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Evidence from Centralized Teacher School Choice in Perú

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Abstract

This paper studies how increasing teacher compensation at hard-to-staff schools can reduce inequality in access to qualified teachers. Leveraging an unconditional change in the structure of teacher compensation in Perú, we first show causal evidence that increasing salaries at less desirable locations attracts teachers who score 0.45 standard deviations higher in standardized competency tests, leading to an average increase in student test scores of 0.33-0.38 standard deviations. We then estimate a model of teacher preferences over local amenities, school characteristics, and wages using geocoded job postings and rich application data from the nationwide centralized teacher assignment system. A policy that sets compensation at each job posting taking into account teacher preferences is more cost-effective than the actual policy in terms of reducing structural inequality in access to learning opportunities, and it possibly enhances the efficiency of the education system.

Keywords: Inequality, Teacher School Choice, Teacher Wages, Matching with Contracts.

JEL Codes: J31, J45, I21, C93, O15.

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1 Introduction

Children born in remote and rural communities face significant disadvantages in achieving comparable levels of academic achievement as their peers born in urban areas (World Bank, 2018). Part of these wide spatial disparities reflect structural differences across geographic areas that are a result of past policies and historical inequities. However, current policies can also contribute to further widening the gap in the formation of human capital if the pre-existing inequality is not compensated for (Glewwe and Muralidharan, 2016).

In this paper, we study how inequality in the access to learning opportunities is amplified or reduced by policies that shape the geographic distribution of one of the most important education inputs: teachers.[1] We shed light on this question in the context of Perú, a developing country with a heterogeneous geography and a population that is characterized by different languages, cultures, and ethnicities. In this context, we document that rigidities in wage setting in the public sector lead teachers to sort on non-pecuniary aspects of employment (Rosen, 1986). Thus, if poorer, more rural communities have less desirable amenities, compensation policies that do not account for teacher preferences can exacerbate prior structural inequality.

We begin our empirical analysis by presenting descriptive evidence on the structural divide in school inputs and academic outcomes between rural and urban areas. In particular, the school system is hard-pressed to staff many small rural public schools scattered throughout the poorest parts of the country. Using detailed administrative data on teacher job applications and job postings, we show that teacher labor supply greatly contributes to the spatial inequality in learning opportunities. Against this backdrop, the government implemented a policy that increased salaries at teaching positions in rural public schools based on a coarse set of school and community attributes.

We exploit discrete jumps in teacher compensation at arbitrary thresholds of the local population to document causal evidence that higher wages significantly increase the demand for both short and long term positions in rural areas. Short term vacancies that offer higher wages in a non-discretionary centralized assignment mechanism are filled with teachers who have higher scores (0.45σ) on the national competency test.[2] However, long term vacancies that offer higher wages but include a discretionary step in the recruitment process are not filled with more qualified teachers in spite of the increased demand. These results indicate

[1] There is ample evidence that teachers matter for student outcomes in e.g., the US (Chetty et al., 2014a; Jackson, 2018), Ecuador (Araujo et al., 2016), Pakistan (Bau and Das, 2020) and Uganda (Buhl-Wiggers et al., 2017).

[2] The increase in teacher quality in high-wage vacancies does not come at the expense of a reduction of qualified teachers on the other side of the threshold of eligibility for the rural wage bonus (see Section 4.5 and 5.4).

that wage policies can shape the spatial distribution of teacher quality but the institutions determining how teachers are evaluated and assigned are also important (Duflo et al., 2015; Estrada, 2019).

The increase in teacher salaries leads to higher student academic achievement in math and language (0.38σ and 0.33σ, respectively). While wages rose for all teachers at eligible schools, test score results are driven exclusively by schools that had open short term vacancies. This pattern and further evidence suggest that higher wages do not prompt an effort response from incumbent teachers, which is consistent with recent findings that show that unconditional wage increases do not affect student outcomes in a setting where most teachers are public servants with permanent contracts (de Ree et al., 2018).[3] The effects on achievement are more pronounced for students at the lower end of the test score distribution. Hence, more qualified teachers are likely to have a larger impact on students at disadvantaged schools.

Taken together, these findings provide credible evidence on the local effects of the policy, which may or may not hold more generally (e.g., in the presence of other wage bonuses and/or equilibrium sorting effects within the assignment system). To evaluate the policy away from the eligibility cutoffs, we propose and estimate an empirical model of teacher school choice taking advantage of teachers' revealed preferences for short term positions. The system follows a serial dictatorship algorithm where job applicants are ranked by their competency scores and sequentially assigned to their preferred school among those that still have an open vacancy. Together with detailed information on every school vacancy, teacher characteristics, and final assignments, this setting is ideal for estimating a flexible model of heterogeneous teacher preferences over wages and job attributes (Agarwal and Somaini, 2020).

The model of teacher school choice is able to replicate the main features of the data in terms of spatial sorting of teachers, including the local effects around the policy-induced wage discontinuity as well as broader trends along the support of the variables that characterize rural areas (e.g., locality population and proximity to the provincial capital). The estimated preference parameters quantify key trade-offs between wages and local amenities, school characteristics, teacher-school match effects, or moving costs. Importantly, teachers belonging to ethnic minorities who predominantly reside in rural areas are more willing to work at schools in communities from their own ethnolinguistic group and thus require a lower compensation to staff those positions.

The model also provides a rich perspective on the effects of the recent reform of the wage

[3] In our context, a large proportion of school vacancies targeted by the wage reform are filled by contract teachers. This feature creates significant flexibility in the labor market thus allowing wage incentives to play an important role in attracting higher quality teachers and consequently improving student outcomes.

schedule on the spatial distribution of teachers in our setting. We show that while most of the impact of the policy on teacher quality happens close to the population threshold its effect on the share of filled vacancies seems spatially concentrated in less desirable locations that are farther away from the cutoffs. We also find that wage bonuses generate, on net, a positive reallocation effect across the entire country, which is explained by the inflow of applicants who are matched to a school vacancy due to the wage incentives.

The changes in predicted teachers' utility associated to matching outcomes with and without the salary increase are markedly heterogenous within geographic areas that pay the same wage, indicating large scope for improvement in the targeting design of the actual policy. We then study alternative compensation schemes using a matching-with-contracts framework (Hatfield and Milgrom, 2005). Within the allocation mechanism that is currently in place for short-term positions, we use the estimated teacher preferences and allow schools to increase the wages they offer sequentially until they fill their vacancies, either unconditionally or conditionally on the quality of the assigned teacher. We show that a policy that sets salaries at each job posting using the information generated by the matching platform is more cost-effective than the actual policy in terms of reducing structural inequality in access to learning opportunities.

The resulting counterfactual wage policy achieves the same objectives of the actual system of wage bonuses at only 10-20 percent of the total cost for the government. We also find that filling every school with at least one teacher would require three quarter of the total wage bill than the actual policy, which instead reaches 80% of that objective. However, shifting the supply of highly qualified teachers towards hard-to-staff schools is significantly more costly. Given the existing stock of prospective teachers and school vacancies, it would take almost seven times the actual budget to assign a teacher in every school with the median competency level of urban areas in the status quo. Such policy objective would require many unassigned, high-quality applicants to accept a teaching position within the system.

Beyond wage incentives, we finally use our framework to benchmark the cost-effectiveness of complementary policy interventions in the labor market of public school teachers. Investing in local infrastructures in our setting would entail achieving our policy objectives at total costs that are 20-30 percent lower. Place-based incentives aimed at enhancing the pool of teachers in locations where the supply is relatively scarce would entail saving 40 percent of the total cost of the policy that assigns a teacher in every school. This last result highlights the predominant roles of moving costs and of the ethnolinguistic match effects in explaining teacher preferences over job postings.[4]

[4] Ajzenman et al. (2021) show evidence that teacher applications to hard-to-staff schools can also be influenced by information interventions or behavioral nudges.

Given that the returns to having a high quality teacher are more pronounced at the lower end of the distribution of learning outcomes, our findings suggest that there is large scope for efficiency gains with respect to the actual policy by reallocating resources towards the most remote rural locations. Under the budget-neutral wage schedule that incentivizes sorting of highly-qualified teachers, we estimate that the share of under-performing students in the most disadvantaged locations would decrease from 80 percent to at most 50 percent.

This paper contributes to a growing literature that uses equilibrium models to study the implications of compensation policies on the spatial distribution of teachers (Boyd et al., 2013; Tincani, 2021; Biasi et al., 2021). There is large body of work studying the effectiveness of pay-for-performance schemes for teachers in both developed and developing countries.[5] Relatively fewer studies consider policy effects of unconditional wage increases on teacher turnover (Clotfelter et al., 2008) and student outcomes (de Ree et al., 2018; Pugatch and Schroeder, 2018; Cabrera and Webbink, 2020). The approach pursued in this paper encompasses these different strands of the literature in so far as we use a combination of a regression discontinuity design and an empirical model of teacher school choice to characterize the effects of unconditional wage increases and the mechanisms through which these effects operated. This framework allows us to go beyond the evaluation of the actual policy implemented in our setting by studying the design of alternative compensation schemes taking into account equilibrium effects.

More broadly, our findings speak to recent work studying different personnel and organizational policies in the public sector (Finan et al., 2017). For instance, Dal Bo et al. (2013) show that increased compensation for public sector positions in Mexico led to a larger pool of applicants, and a higher quality of hired employees. In Uganda, Deserranno (2019) finds that higher financial incentives attract more applicants and increase the probability of filling vacancies while crowding out pro-socially motivated health workers. We add to this literature by incorporating an empirical market design approach (Agarwal and Budish, 2021), which leverages matching platforms to study the design of compensation schemes in the public sector.[6]

2 Data

In this paper, we combine several administrative data sources from the Ministry of Education of Perú over the period 2015-2018. While the resulting dataset spans the universe of public-

[5] See for example Muralidharan and Sundararaman (2011); Barrera-Osorio and Raju (2017); Gilligan et al. (2022); Leaver et al. (2021); Brown and Andrabi (2020).

[6] This approach was pioneered in Agarwal (2015, 2017) in the context of the market for medical residents in the United States.

sector teachers and schools, we restrict our analysis to primary schools for two reasons. First, secondary schools are much less prevalent in rural areas. Public schools serve 74% of the primary school enrollment countrywide. In rural communities (i.e., those with less than 2,000 inhabitants), public schools are generally the only option.[7] To the extent that the geographic distribution of schools is key to understanding disparities in access to competent teachers, we need to focus on primary schools that are well represented throughout the country. Second, in primary schools, all students in a classroom are taught by a single teacher, instead of having one teacher for each subject. This setup allows us to more precisely match students and their teachers, and estimate the effect of the newly assigned teachers on student achievement in the empirical analysis in Section 4.

Our first data source is the *centralized teacher job application and assignment system*. This dataset includes information on all job vacancies posted at every public school in the country during the first two rounds of the national recruitment of public sector teachers (2015 and 2017), the scores in the standardized evaluations for every applicant, and detailed information on all the steps of the job application process that we discuss in Section 3.2. Figure A.1 shows some relevant individual-level correlates of teacher performance in the standardized test. During the first (second) national recruitment drive, 64,000 (72,000) applicants competed for 18,000 (25,500) vacancies in primary schools. Table A.1 reports basic descriptive statistics on applicants across types of contracts in the public sector. About 8% of the applicants report no prior teaching experience (neither in the public sector nor in the private sector). More than one-fourth of the applicants in our sample report speaking *Quechua* or *Aymara* as their main language, thus likely belonging to the ethnic groups that are concentrated in the Andean highlands, while an additional 2% belong speak one of the many other languages spread in the Amazon forests.[8]

Our second administrative data source is the *teacher occupation and payroll system (NEXUS)*. This is a longitudinal dataset collected and maintained by the Ministry of Education, which contains the complete records of all teachers employed in the public sector. In particular, the dataset includes individual identifiers for all teachers, the school in which they work (but not the specific grade), and the type of contract/position they hold (permanent or contract, number of hours, etc.). This information is collected at the start, middle, and end of each school year, allowing us to precisely trace both the school of origin (if any) and the school of destination (if any) for each applicant to the national recruitment drives. About two-third of the applicants had previously been employed as public sector teachers.

[7] There are more than 6,000 public primary schools in rural areas catering to 98 percent of school-aged children in 2015.

[8] The information on the main language spoken by the applicants is only available for the 2015 recruitment drive.

We obtain data on school and locality characteristics from the national *school census*. These data include information on the number of students, school infrastructure (libraries, computers, classrooms, sports facilities), and staff (teaching and administrative) at each school. Additionally, the dataset includes information on local amenities, e.g., access to basic services (electricity, sewage, water source) and infrastructure (community phone, internet, bank, police, public library). This information is reported annually by school principals. Table A.2 reports basic descriptive statistics for some key school characteristics for urban and rural areas, respectively.

Our fourth data source is the administrative records on *student academic outcomes*. The *Evaluación Censal de Estudiantes* (ECE) is a national standardized test that covers curricular knowledge of math and language (Spanish). The test is administered by the Ministry of Education at the end of every school year at selected grades at both public and private schools with an enrollment of more than five pupils. We have access to individual test scores from 2014–16 and 2018 for fourth grade students in public primary schools (widespread floods in the country led the government to cancel the 2017 exams).

Finally, in collaboration with the Ministry of Education, we administered an online survey among the applicants to the permanent teaching positions during the 2015 centralized job application process. The response rate is slightly below 20% (5,553 applicants), and observable teacher characteristics of respondents are not different from those that did not respond. Among several questions on teachers' application decisions, we asked applicants to rank the their preferred school's characteristics. As shown in Panel B of Table A.3, 44% of teachers say "being close to home" is one of the key characteristics guiding their preference ranking. Other often cited attributes of the teaching job are prestige, safety and "cultural reasons". While "prestige" is admittedly a somewhat vague concept, "cultural reasons" mainly refers to ethnolinguistic similarities between teachers and the communities where the schools are located. Interestingly, distance and prestige are disproportionately appreciated by teachers who scored the highest grades (top quartile) in the centralized test, compared to the average teacher. These survey results partly motivate the empirical model that we propose and estimate in Section 5.

3 Context and Institutions

3.1 Inequality of Education Inputs

Perú is a country that spans a vast and varied geography, which includes mountainous areas in the Andes, the Amazon forest, and coastal regions. It is composed of culturally and linguistically diverse people, who have lived under extractive systems of governance as a Spanish colony. The legacy of colonial institutions and policies is one of the root causes of current structural inequalities. These previous policies were often targeted to the highlands and jungle regions, where most of the natural resources are located. Currently, those areas show high poverty rates and a large concentration of indigenous people.

Over the last decade, the government has undertaken several efforts to improve educational outcomes in poor, rural areas, such as implementing a large-scale conditional cash transfer program, investing in school infrastructure projects, and improving access to drinking water and sewage (Bertoni et al., 2020). However, large differences still exist in the access to educational inputs such as school infrastructure. In Table A.2 we document some differences between schools in urban and rural areas across a broad set of indicators of schools, teachers, students, and community characteristics. Schools in rural areas predominantly hold (90%) mixed classes, with a single teacher serving students of several grades at the same time. About one-third of the rural schools lack access to basic services such as running water or electricity.

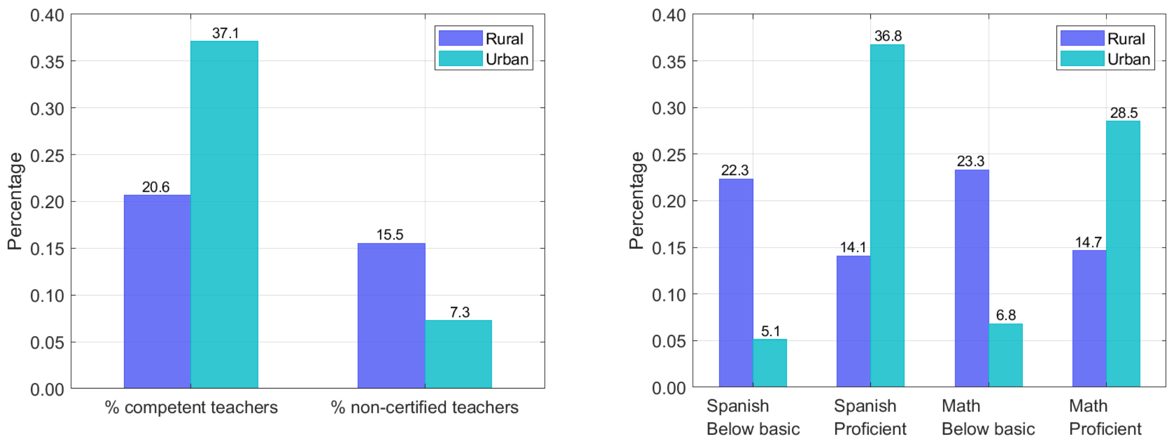
Figure 1 documents the stark differences in teacher quality and student achievement between urban and rural primary schools. Panel A shows that teachers at rural public schools are half as likely to pass the requirements set by the government for permanent teachers ("competent teachers"), and are twice as likely to lack teaching credentials (non-certified teachers).[9] Panel B of Figure 1 displays students' academic performance on the national standardized evaluation in two subjects – Spanish and math. Approximately one in four students enrolled in rural schools are classified as performing below the basic curricular requirements in either of the two subjects, whereas the corresponding shares in urban schools are only around 5%.

Figure A.2 shows the geographic distribution of competent teachers across provinces alongside the corresponding distribution of student test scores. Competent teachers are heavily concentrated in the richer, coastal cities, while they are nearly absent in the highlands and the inner amazonian regions (Panel A). The spatial variation in students' achievement outcomes, shown in Panel B of Figure A.2, is almost a mirror image of the spatial distribution of competent teachers across the country.

We document inequality in schooling inputs and outputs across Perú. While local ameni-

[9] Competent teachers are defined in Figure 1 as those who attain a score of at least 60% in the curricular and pedagogical knowledge module of the standardized test used to both screen and recruit teachers (see Section 3.2). Subject competency test have shown to correlate with teacher value added and other dimensions of teacher quality in several contexts (Bold et al., 2017; Estrada, 2019; Gallegos et al., 2019; Araujo et al., 2020). For the Peruvian case, Bertoni et al. (2021) document strong correlations between various measures of teaching effectiveness and the score in the curricular and pedagogical knowledge module of the evaluation test.

Figure 1: Teachers and Students in Urban Vs. Rural Areas



a) Teachers **b) Students**

NOTES: These figures show different summary statistics about teachers and students in urban and rural areas. Panel A shows, separately for rural and urban schools, the average share of teachers classified as competent based on the curricular and pedagogical knowledge of their subjects of specialization and the average share of teachers who lack teaching certifications. Panel B shows how academic performance in the Spanish and math modules of the national standardized evaluation differs between students of urban and rural schools. Table A.2 in the Appendix presents a broader set of indicators for school and community-level characteristics across urban and rural areas.

ties and school infrastructures likely reflect structural differences between urban and rural areas, the unequal spatial distribution of teacher quality suggests a margin where policy can play an important role. To better understand the reasons behind the current allocation of teachers across different geographic areas, we now describe the institutions that govern the labor market for public school teachers.

3.2 Contracts, Wages, and Sorting of Public School Teachers

Public school teachers in Perú are hired under two distinct types of contracts. Permanent teachers (*docentes nombrados*) are civil servants with stable employment conditions (i.e. indefinite contracts). Alternatively, teachers can be hired by the central administration to work at a specific school for an academic year as contract teachers (*docentes contratados*). This contract has the option of being renewed for up to one more year, conditional on being approved by the school's administration. Short-term contracts are routinely used in most education systems around the world and are often designed as entry-level positions in the teaching career.[10] In our setting, about one out of five primary school instructors in urban

[10]Research in India and Kenya shows that locally hired teachers on annual contracts have better performance, and their students score higher in standardized test scores (Muralidharan and Sundararaman, 2011; Duflo et al., 2015), although in Kenya these gains tend to vanish when the contracts are administered by the government, rather than by a non-government organization (Bold et al., 2018).

areas is hired as a contract teacher, while these contracts are more widespread in rural areas, where they reach almost half of the labor force in the most remote schools.

The compensation of public-school teachers in Perú depends on (i) the type of contract (permanent or contract teacher), (ii) seniority, and (iii) specific location or school characteristics. In 2016, the base monthly wage for primary-school teachers under a short-term contract was S/ 1,396 (US$ 402), while that for permanent teachers was S/ 1,550 (US$ 447), although more experienced permanent teachers can earn up to S/ 4,043 (US$ 1330). Additional wage bonuses are given to all teachers (irrespective of the contract) working in specific types of schools, such as multi-grade or single-teacher schools, or schools located in disadvantaged communities.[11] According to the national household survey (ENAHO 2016), the earnings of primary school teachers are ranked second to last among the liberal professions in Perú, followed only by translators and interpreters. Nationally representative survey data on teachers (ENDO 2014) document that the average monthly wage for teachers working in primary schools in the private sector is approximately S/ 950. Only private school teachers in the top ten percent of the distribution earn more than the base wage of a teacher in the public sector.

Permanent and contract teachers in Perú were recruited in a decentralized fashion until 2015. As in most countries, regional and local level officials often had significant discretion in teacher hiring and allocation decisions (Bertoni et al., 2019; Estrada, 2019). In an effort to make the process more transparent and meritocratic, the Ministry of Education established a nation-wide recruitment process in which school-level job postings and teacher job applications are processed on a single, centrally-managed platform. The first national recruitment drive took place in 2015, followed by another round in 2017. Teachers recruited through the 2015 and 2017 drives started teaching in the 2016 and 2018 academic years (March-December), respectively.

The recruitment process is structured in two phases.

Permanent teacher recruitment. Every vacancy for permanent teachers across all education levels are posted in a centralized platform. The opening of each of these positions depend on previous retirements and transfers and the ability of local governments to secure permanent funding for the position. Applicants are required to have a teaching accredita-

[11]Figure A.3 shows the different wage bonuses, which vary between 4% (bilingual school) and 36% (extremely rural locations, as defined in Section 3.3) of the monthly base wage. Schools can satisfy multiple criteria (e.g. multi-grade and bilingual), in which case the bonuses are cumulative. Accredited bilingual teachers are eligible for an additional bonus of S/ 100. There are also some compensation adjustments throughout the year, such as a holiday bonus, which usually represents less than 5% of the total monthly wage. The wage bonuses for multi-grade and single-teacher schools were cancelled in 2017 and reinstated in 2020.

tion (i.e. a teacher degree) and to have taken the standardized competency evaluation.[12] Those who correctly answer at least 60 percent of the questions in each of the three parts of the test are eligible for a permanent position, and can in turn submit a ranked-order list of school preferences of up to five available positions within a given school district.[13] In our data, about 10% of the applicants are eligible for a permanent teaching position. Once preferences are submitted, teachers move on to a decentralized stage of evaluation in which each school interviews a short-list of the highest scoring teachers who express a preference for that vacancy. In this second evaluation, teachers are given another score based on their performance in a typical class that they have to teach and an in person interview with the principal and other school stakeholders. Additionally points can be also assigned based on their CV. Permanent positions are finally allocated based on an overall score that comprise the competency test and the decentralized evaluation.

Short-term/contract teacher recruitment. The goal of this stage is to fill as many of the remaining positions with a certified teacher. About half of the applicants who cleared the bar to be eligible for permanent positions eventually participated in this round of the assignment mechanism. These are mostly teachers who were not selected for their preferred positions and thus opted for a temporary position. Importantly, these teachers are not systematically different to those who are assigned to a permanent position (see Table A.1). Unlike the assignment of permanent teachers, short-term teaching positions are allocated through a serial dictatorship algorithm. In this mechanism, school preferences are taken to be a strict ranking of teachers' competency scores. Applicants sequentially (starting by the highest ranked) choose from the list of open vacancies in a given school district. Once a vacancy is filled, it is eliminated from the list of the available options in that district, and the next lower-ranked teacher is allowed to pick her preferred option. This iterative process continues until all vacancies are filled, or until the lowest-ranked teacher in each school district is allowed to choose among the remaining vacancies. After the first round of the matching process, unassigned applicants are given another chance to choose among the remaining open vacancies from other districts. Positions that are not filled through the serial dictatorship mechanism are eventually filled through a decentralized secondary market,

[12]The test is divided into three modules, which carry different weights in the total score: logical reasoning (25 percent), reading comprehension (25 percent), and curricular and pedagogical knowledge (50 percent).

[13]In the 2015 screening and recruitment process, candidates were allowed to rank a maximum of five schools. This constraint was removed from 2017 onwards, and applicants were free to submit an unlimited number of options. In total there are 218 school districts. There is substantial within-district variation in the rural status of the school vacancies. For the average school district, 71 percent of vacancies are in rural locations. In 33 school districts all available vacancies are in urban locations (15 percent).

where non-certified teachers are also included.[14]

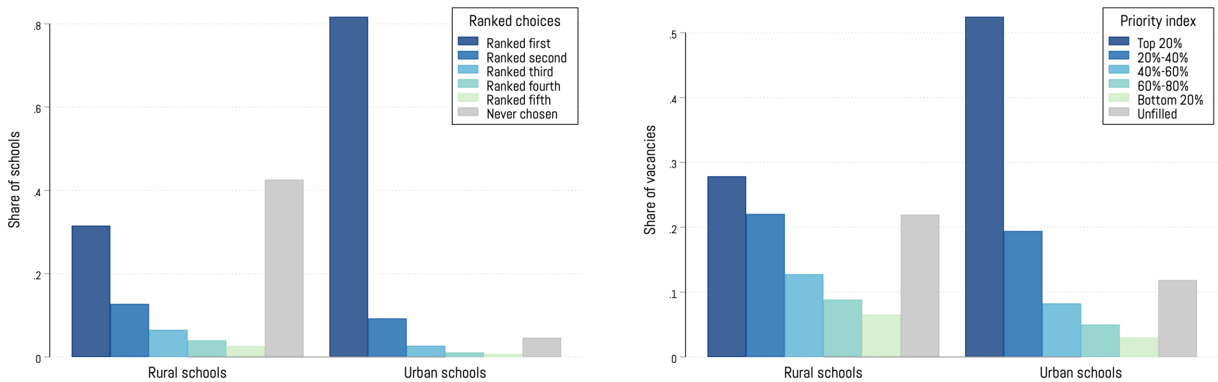
Figure 2 shows data from the applications to primary-school vacancies, showing teachers' preferences for different types of schools. While 80% of schools in urban areas are ranked first by at least one applicant to a permanent position, vacancies posted in rural areas receive significantly fewer applications – nearly half of rural schools are never even ranked in applicants' preference lists. As a result, more than two-thirds of job vacancies for permanent positions remain unfilled in rural schools, while three-fourths of vacancies are filled in urban schools through the centralized assignment mechanism. Panel B considers the sample of contract teacher positions by plotting the quintiles of the priority indices for the positions that are filled in the serial dictatorship algorithm. Short-term teaching vacancies in urban areas are in higher demand, as more than half of these postings get filled by teachers ranked in the top 20% of the pool of applicants in their respective school districts whereas the distribution of the assigned teachers at short-term vacancies in rural areas is clearly more skewed toward less qualified personnel (as measured by the competency score). Overall, the centralized assignment process fills almost 90 percent of short-term vacancies in urban areas and slightly less than 80 percent of short-term vacancies in rural areas.[15]

We conclude that the spatial inequality in access to qualified teachers displayed in Panel A of Figure 1 can be (at least in part) explained by teachers' preferences and choices over locations. Teachers in poor rural areas face numerous challenges: scarcity of basic school inputs, lack of services and public goods, few local amenities, and (for some) being far from friends and family. To the extent that wage-setting protocols do not compensate for the lack of these amenities, these jobs will be less attractive. Indeed, the data on job postings and teacher rank-order applications show that applications are skewed toward positions in urban areas, and the system is hard-pressed to staff the roughly 14,000 positions in rural public schools in the poorest parts of the country. As a consequence, many of these vacancies are eventually filled using short-term contracts by teachers who, on average, have competency scores that are 0.5 standard deviations lower than those assigned to urban schools, while the remaining portion are filled by non-certified teachers through the decentralized secondary market.

[14] Over 53,000 applicants for short-term teaching positions (88%) were not assigned within the first two (centralized) rounds of the 2015 assignment mechanism. More than three-quarters of them re-applied in the 2017 assignment mechanism.

[15] While on average there are seven applicants per vacancy within the centralized application platform, there are more than two vacancies per applicant in indigenous communities in the forest inlands, which explain the reason why these vacancies are more likely to remain unfilled (50% vs. 21% in the overall sample).

Figure 2: Teacher Choices over Job Postings



a) Permanent Teachers **b) Contract Teachers**

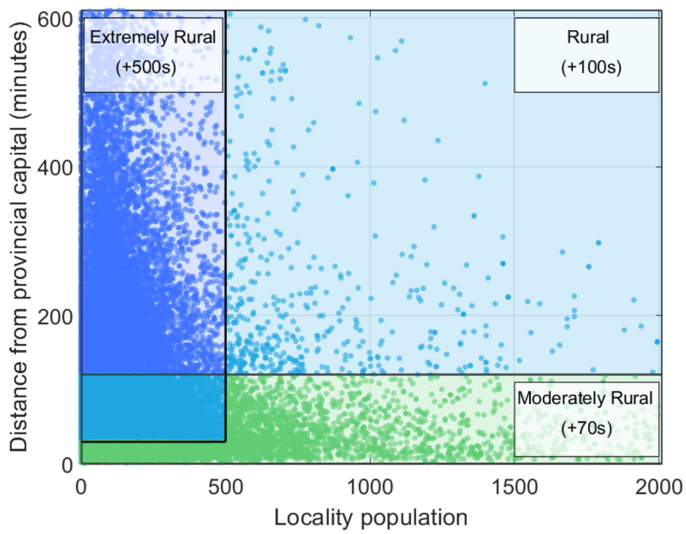
NOTES: This figure depicts the demand for teaching positions in rural and urban schools. Panel A plots the relative share of schools by the highest preference received, so that "ranked first" means that at least one teacher from among all applicants ranked it as number one, "ranked second" means that no teachers ranked the school as number one, but at least one teacher ranked it as number two, and so forth. Similarly, the grey bar indicates the relative share of schools that were not mentioned in any of the permanent teacher rankings. Panel B plots the priority order (grouped in quintiles of the teacher competency score) in which a short-term position is filled, together with the share of vacancies that remained unfilled (not filled by a certified teacher). The numbers are obtained by pooling the data from the two recruitment drives from 2015 and 2017.

3.3 Policy Changes to Compensation in Rural Locations

The government recently implemented a reform to the wage bonus that significantly increased teacher compensation at positions in select rural schools. The new policy established three distinct categories of rurality according to the school locality's population and its proximity to the provincial capital (see Figure 3). The population of the locality is measured by population counts in the latest available census (2007). Travel time from the locality to the provincial capital is used as a proxy for how remote a community is, and it is computed based on the school's GPS coordinates, the types roads available at the time of the measurement, and the most frequent modes of transport. *Extremely Rural* schools are those in localities with less than 500 inhabitants, and for which it takes more than 120 minutes to reach the province capital. The second category of schools, labeled as *Rural*, is reserved for either: (a) schools in localities with less than 500 inhabitants and are located between 30 and 120 minutes from the province capital, or (b) schools in localities with 500–2,000 inhabitants that are farther than 120 minutes from the province capital. The third category of *Moderately Rural* schools are either: (c) in localities with 500–2,000 people that are within 120 minutes of the province capital, or (d) in localities with less than 500 inhabitants which are within 30 minutes of the province capital. All other schools are classified as Urban, and are therefore not entitled to the wage bonus.

Rurality bonuses were first introduced in January 2014, and only permanent teachers

Figure 3: The Distribution of Rural Schools and the Wage Bonuses



Notes. This figure shows the spatial distribution of rural primary schools along the two dimensions that determine assignment of the rural wage bonus. *Extremely Rural* schools are the dark blue dots, *Rural* are light blue and *Moderately Rural* schools are green.

were eligible to receive them. In August 2015, the wage bonuses were extended to contract teachers. Importantly, these changes were only announced briefly before they were actually implemented (in August, i.e. in the middle of the school year) and thus right before the first centralized recruitment drive (October 2015), which marks the start of our study period. The bonus for *Extremely Rural* schools is fairly generous: for contract teachers, it ranges between 25 and 36 percent of the base wage, depending on the school year considered (contract teacher wages increased from S/ 1,396 in 2016 to S/ 2,000 in 2017); for permanent teachers, it ranges between 25 and 32 percent of the base wage.

Figure 3 displays a scatter plot of the distribution of the 25,000 rural primary schools in Perú over the population (x-axis) and the proximity to the provincial capital of the communities where the schools are located (y-axis). There is a large mass of schools around both the time cutoffs (30 minutes and 120 minutes from the provincial capital) and the population cutoff (500 inhabitants) for the rural wage bonuses. As the localities become more remote, schools are more likely to be located in communities that are small and predominantly fall into the *Extremely Rural* category. Likewise, for localities with populations above 1,000 inhabitants, there are more communities that are closer to the provincial capitals (*Moderately Rural*).

4 Causal Effects of the Increase in Compensation

4.1 Regression Discontinuity Design

Offering higher wages for positions at rural locations could potentially lead to better student outcomes through two main mechanisms. On the one hand, at the extensive margin, higher wages could attract more and higher-quality teachers. On the other hand, higher levels of compensation may also motivate incumbent and newly hired teachers to exert higher levels of effort. Our empirical analysis identifies the causal effects of unconditional wage increases on teacher application behavior, teacher selection, and student outcomes. We do this by exploiting the classification rules of the rural wage bonus, and compare (i) the characteristics of teachers who choose/are assigned to a position at a high vs low paying school, and (ii) student test scores between schools that offer high vs low compensation to their teachers. Additionally, to discern whether changes at the extensive or at the intensive margin of teacher quality can explain the effect of the wage reform on students' academic achievement we can compare student outcomes in schools with and without open vacancies in the national recruitment drives.[16]

The introduction of the rural wage bonus may generate incentives for school principals and administrators to manipulate the information used to determine bonus eligibility. The population threshold is based on census data, and as such, it is difficult to manipulate, whereas the time-to-travel measure is gathered by inspectors from the Ministry of Education, who physically go to the schools and take the GPS coordinates of the school's location. The procedure was originally done in 2014 and then repeated in 2017 to account for possible changes in the transportation network. By the time the information was to be updated, the previous measurement had become public information, and hence some schools located just below the 120-minute threshold may have gained eligibility to the S/ 500 wage bonus by slightly manipulating the GPS measurement. The data shows that there is a significantly larger mass of schools that falls just above the time-to-travel threshold for the assignment process that took place in 2017, while there are no significant jumps in the density of schools at the population threshold for either of the years of interest (see Figures B.1, B.2, and

[16]Table B.3 shows that there is no effect of the wage bonus on the probability that a school has an open position for permanent or contract teachers. Figure A.4 displays scatter plots similar to the one reported in Figure 3 for schools with and without vacancies in the national recruitment drives of 2015 and 2017, respectively.

B.3).[17]

We thus rely on the population-based assignment rule as the only source of exogenous variation in teacher wages for this part of the analysis. Table B.1 shows the estimated wage increases explained by crossing the population threshold. Contract teachers in localities with slightly less than 500 inhabitants earn on average over S/ 250 more than those in localities that are just above the cutoff. This represents an increase in the monthly wage of about 13 percent. The corresponding average increase in wages for newly recruited permanent teachers (i.e., no experience) due to the rural bonus reform is S/ 225, or 11 percent of their monthly wage.[18]

Given continuity of potential outcomes around the population cutoff, the following specification identifies the effect of a higher wage bonus:[19]

$$y_{jt} = \gamma_0 + \gamma_1 \mathbf{1}(pop_{jt} < pop_c) + g(pop_{jt}) + \delta_t + u_{jt}, \tag{1}$$

where y_{jt} is an outcome variable for school j at time t, $g(\cdot)$ is a flexible polynomial in the population of the locality of the school at both sides of the population cutoff, δ_t denotes time indicators for the specific year of the recruitment drive (included only for teachers' outcomes), and u_{jt} is an error term clustered at the school$\times$year level for teachers' outcomes and clustered at the school level for students' outcomes (that we observe in only one year, see Section 4.4). The parameter of interest is γ_1, which represents the average outcome difference between schools, teachers, or students in localities that are just above or below the population cutoff, and therefore that are marginally eligible to receive (or not) an unconditional increase of about 15% in teacher wages. We estimate γ_1 non-parametrically using the robust estimator proposed by Calonico et al. (2014) through bias-corrected local linear regressions that are defined within the mean squared error optimal bandwidths.

We exclude from the estimation sample all urban and rural schools in localities within 30 minutes of the province capital since for them, crossing the population cutoff does not

[17] While the locality population is a good predictor for the eligibility to the rural wage bonus in both years, time-to-travel in 2015—which we observe to be less prone to manipulation—does not help predict the policy eligibility status in 2017 and therefore doesn't provide useful variation for estimating the effects of the wage bonus in 2017 (see Figure B.4). An alternative strategy would be to limit the sample to observations that are above the 120-minute time-to-travel cutoff, however, this implies conditioning on a partially manipulated variable. This sample restriction would also exclude a large portion of schools, and in particular, some located in the lower-right quadrant of Figure 3, thereby missing relevant variation in wages in the data.

[18] These effects are unconditional weighted averages –pooled across school years– of the different wage increases induced by crossing the population cutoff from above for different values of the time-to-travel variable.

[19] Table B.2 shows that pre-determined school and locality-level covariates are smooth around the population threshold, with point estimates that are very small and not statistically different from zero in all but five cases for 2015, and in all cases for 2017 (29 covariates considered).

lead to an increase in the bonus. We further restrict the sample to schools with non-missing observations for the different outcome categories considered in our analysis. We present all the results pooling the data from the two recruitment drives from 2015 and 2017. The results split by year are shown in Tables B.4 and B.5 and are broadly consistent with the patterns described in the main text.[20]

4.2 Teacher Choices over Job Postings

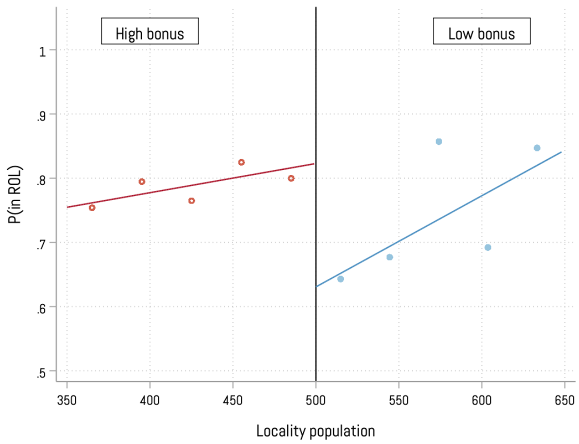
We start by showing how teachers' application behavior is affected by higher wages, providing direct evidence on the effects of wage increases on teachers' labor supply decisions. We document graphical evidence of the threshold crossing effects separately by job applications for permanent and short-term teaching positions. Panel A of Figure 4 documents clear evidence that applicants for permanent teaching positions are more likely to include in their applications schools in localities with a population just below the cutoff (eligible for a higher wage bonus), as opposed to options just above (not eligible for a higher wage bonus). Away from the cutoff, the observed positive correlation between teachers' choices over job postings and the population of the community is consistent with the notion that the population captures some valuable amenities in the locality.

Panel B considers the choices over job posting for contract teachers. As in Section 3.2, we infer teachers' preferences over positions from choices observed in the serial dictatorship. To do this, we normalize the ranking in which a position is chosen within a school district, so that the index takes the value of zero if the position is filled last and one if the position is filled first. Short-term positions that are just below the population cutoff get filled at higher priority order when compared to those above the cutoff, which again indicates that the wage bonus increases the demand for these positions.

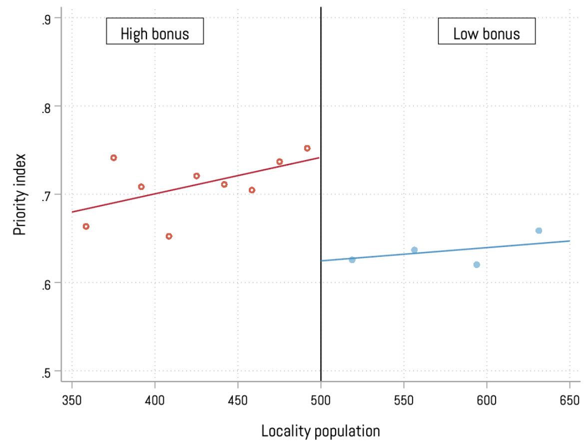
Table 1 reports the corresponding regression-discontinuity (RD) estimates from the empirical specification in equation (1) using data at the school/vacancy level. In Column (1) the dependent variable is either an indicator that takes the value of 1 if a school was mentioned in at least one application for a permanent teaching position (Panel A) or the normalized priority index at which a short-term position is filled (Panel B). In the neighborhood of the population discontinuity defined by the MSE-optimal bandwidth (RD sample), the average school is mentioned in 76% of permanent teacher rankings. This proportion increases by 19 percentage points for schools that offer higher wages. Similarly, the average short-term position in localities with a population slightly above 500 inhabitants is filled by a teacher ranked in the 37^{th} percentile $(1 - 0.63)$ of the score distribution of applicants, while schools

[20]The main estimates reported in this section are robust to alternative specifications and estimation choices. The results of these specification checks are reported in Figures B.5 and B.6.

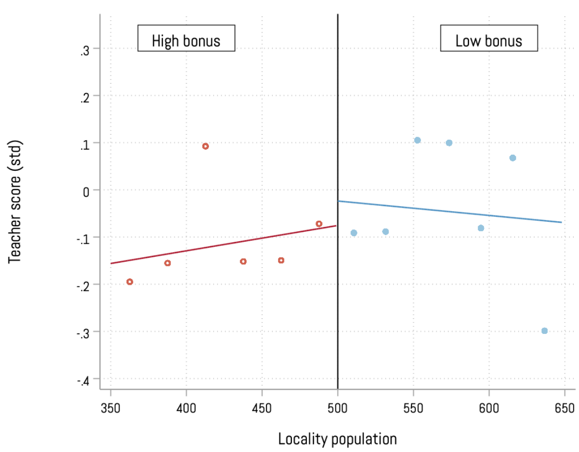
Figure 4: Teacher Choices over Job Postings



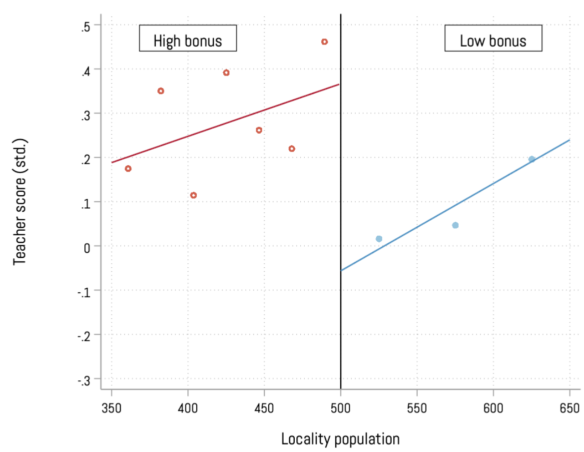
a) Stated Preferences, Permanent Teachers



b) Revealed Preferences, Contract Teachers



c) Competency Score, Permanent Teachers



d) Competency Score, Contract Teachers

Notes. This figure shows how applicants' preferences and quality vary based on the difference between the 500-inhabitants cutoff and the population of the community where the school is located. Panels A and C focus on the assignment process of permanent teachers. In Panel A the outcome variable is a dummy equal to one if a school was mentioned in at least one application, while in Panel C the outcome variable is the standardized (total) score obtained in the centralized test by the newly-assigned permanent teacher. Panels B and D are analogous to A and C for the assignment process of contract teachers. Panel B uses as outcome variable the priority in which a vacancy was chosen in the serial dictatorship mechanism (normalized so that it takes value from zero to one), while Panel D uses the standardized score obtained in the centralized test by the newly-assigned contract teacher. Each marker indicates the average of the outcome variable within each bin, defined following the IMSE-optimal evenly spaced method by Calonico et al. (2015). Solid lines represent the predictions from linear regressions estimated separately for observations to the left and to the right of the cutoff.

that offer a wage bonus manage to fill the position with an applicant in the 24^{th} percentile $(1 - 0.63 - 0.13)$.

The priority index of contract teachers reported in Column (1) and the competency scores for both permanent and contract teachers reported in Column (3) of Table 1 are defined for

Table 1: Teacher Choices and Sorting

Panel A: Sample of Permanent Teachers			
	(1) Stated Preferences	(2) Vacancy filled	(3) Competency score
High Bonus	0.188	0.026	-0.037
	(0.069)	(0.074)	(0.155)
Bounds			[-.302; .205]
Mean dep. var. (Low Bonus)	0.755	0.371	-0.080
Bandwidth	166.986	169.330	259.213
Schools	835	847	830
Observations	1009	1725	1167
Panel B: Sample of Contract Teachers			
	(1) Revealed Preferences	(2) Vacancy filled	(3) Competency score
High Bonus	0.130	0.051	0.483
	(0.036)	(0.048)	(0.124)
Bounds	[.116; .138]		[.391; .5]
Mean dep. var. (Low Bonus)	0.634	0.900	0.063
Bandwidth	150.781	159.432	152.768
Schools	836	935	851
Observations	1917	2199	1955

Notes. This table reports the effect of crossing the population threshold on different outcomes. Panel A uses the sample of permanent teachers. In Column (1) the outcome variable is a dummy equal to one if a school was mentioned in at least one application, while in Column (2) is an indicator for whether the vacancy was filled by a certified teacher in the assignment process for permanent teachers. The regression displayed in the last column uses the standardized competency score obtained by the teachers in the centralized test as outcome variable. Panel B focuses on the selection process of contract teachers. Column (1) shows the effects on the rank in which a vacancy was chosen in the deferred acceptance mechanism (normalized so that it takes values from zero to one), while Columns (2) and (3) are analogous to those from Panel A. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. In Column (1) of Panel A and in Column (3) the sample is restricted to vacancies that were actually filled by a certified teacher. In those cases, the table also reports the RD bounds estimated using the procedure developed in Gerard et al. (2020). The table also reports the mean of the dependent variable computed within the interval $(-BW, 0]$ (Low Bonus). Standard errors are clustered at the school$\times$year level.

the subset of the open vacancies that got filled in the centralized stages of the matching process. To deal with this potential endogenous selection into the sample, we report RD bounds below the point estimates using the approach outlined in Gerard et al. (2020). The bounds are in general quite tight, thereby suggesting that the censorship in the density of the observations due to the fact that some vacancies remain unfilled is inconsequential for the RD estimates.

The evidence presented in this subsection show that vacancies at schools that receive a higher wage bonus become more desirable: They are requested more often by applicants for permanent positions and are filled faster by contract teachers. The increased competition for vacant positions can lead to an increase in the quality of applicants who select into these higher-paying jobs and/or an increase in the quantity of teachers matched to those rural vacancies. In turn, we explore these potential margins of response to the wage reform in the next subsection.

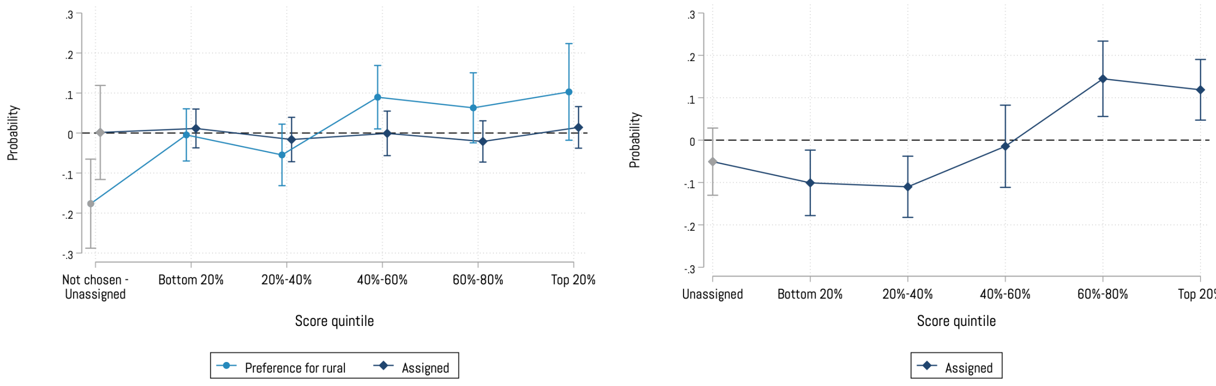
4.3 Teacher Sorting Patterns

A first-order objective of the centralized assignment system is to fill as many position as posible. If the vacancies go unfilled, schools either recruit teachers without credentials or increase the workload for the existing teachers at the school, presumably reducing their effectiveness. Column (2) of Panel A in Table 1 presents regression-discontinuity estimates for the probability that a vacancy is filled in the selection process of permanent teachers, while Panel B shows analogous estimates for contract teachers. Permanent teacher positions that offer higher wages are not more likely to be filled, compared to those offering lower wages. For contract teachers, instead, we find a positive but not statistically significant effect of higher wages on the probability that a vacancy is filled. This evidence can be reconciled with the "local" nature of the estimates shown here. While it may be the case that higher wages induce some teachers to accept a position in a more disadvantaged location, this margin of response to the wage bonus may be active elsewhere in the spatial distributions of schools shown in Figure 3. Indeed, 90% of the rural vacancies are filled in the low bonus areas of the RD sample. In Section 6.1, we address this issue directly by simulating the global sorting patterns triggered by the system of wage bonuses currently in place using the estimated model of teachers' preferences that we discuss in Section 5.

We next investigate whether the observed boost in competition for high-paying positions in extremely rural locations leads to an increase in teacher quality, as measured by the competency score used to define priorities in the assignment algorithm. The two-sided nature of the assignment process for permanent teachers may possibly explain the small and insignificant effects of a higher wage bonus on the quantity and quality of realized matches in *Extremely Rural* schools, as reported in Figure 4 (Panel C) and in Column (3) of Table 1 (Panel A). Figure 5 shows estimates reflecting the preferences and final assignments of permanent teachers (Panel A) and contract teachers (Panel B) for the different quintiles of the test score distribution. Schools offering higher bonuses are more likely to be included in the ranked-order lists of more competent teachers (light blue line in Panel A). However, this change in demand triggered by the wage incentives does not translate into a disproportional assignment of higher quality teachers in these schools (dark blue line in Panel A). The decentralized stage of the assignment mechanism may have potentially undone the positive sorting toward disadvantaged locations induced by higher wages.

Both the graphical evidence displayed in Figure 4 (Panel D) and the RD estimates in Column (3) of Panel B of Table 1 show that contract teachers who select into schools that

Figure 5: Wage Bonuses and the Selection of Competent Teachers



a. Permanent Teachers **b. Contract Teachers**

Notes. The figure displays the effect of crossing the population threshold on different measures of the demand for teaching positions and the resulting quality of the recruited teachers. Circles in panel A indicate the point estimates from a set of regression of the form of Equation (1) where the dependent variable is either a dummy equal to one if a school was not mentioned in any application for a permanent teaching position or a set of binary indicators for whether the school was mentioned by at least a teacher whose score falls into the quintile of the distribution of the competency score reported on the x-axis. Similarly, diamonds in Panel A and B are the point estimates from a set of regressions where the dependent variable is either a dummy equal to one if a teaching position remained unfilled, or was filled by a non-certified teacher, or a set of binary indicators for whether the vacancy is filled by a teacher whose score falls into the quintile of the distribution of the competency score reported on the x-axis. Markers and vertical lines indicate the robust bias-corrected regression-discontinuity estimates and confidence interval (at the 90% level) obtained using the robust estimator proposed in Calonico et al. (2014).

offer a higher wage bonus have higher competency scores, on average, than those who choose a position in another rural school. The magnitude of the effect is 0.48 standard deviations of the distribution of the competency score, a very large effect, which points towards quantitatively important sorting implications within the assignment system. The magnitude of the effect is consistent with the fact that a larger proportion of teachers in the top two quintiles of the test score distribution disproportionally sort into higher paying positions (see Panel B of Figure 5). To put this magnitude in perspective, the average gap in teachers' competency between *Extremely Rural* schools and other rural schools is approximately 0.3 standard deviations, whereas the average gap between rural and urban schools is about 0.5 standard deviations.

In sum, a higher wage bonus targeted at disadvantaged locations shifted applications toward schools offering both permanent and short-term positions. This change in teachers' labor supply does not seem to significantly affect the probability of creating new matches. While for permanent teachers this result is arguably due to the design of the assignment mechanism, for contract teachers it can be explained by the fact that there is little scope for a substantial increase in the share of filled vacancies at the margin. Increased compensations in rural schools leads, instead, to a large inflow of more competent teachers for short-term positions.[21]

4.4 Student Achievement

To the extent that contract teachers account for nearly half of the teaching positions in the RD sample (where each school has three teachers, on average), the increased quality of new teachers documented in the previous subsection may generate substantial improvements in student learning outcomes. We document this effect by implementing the same empirical strategy we used to identify the causal effect of compensation on teachers' outcomes. Hence, we compare student test scores in schools in localities that have less than 500 inhabitants with those with a slightly larger population. In Table 2 we report separate results for standardized test scores in Spanish (Panel A) and math (Panel B) administered to fourth graders three years after the policy change. We focus on test scores collected at the end of the 2018 academic year, since this increases the likelihood that any given cohort of students in fourth grade has been exposed to teachers recruited through the centralized system after the introduction of the rural wage bonuses.[22]

Recall that wage bonuses apply to both incumbent and newly recruited teachers in an eligible school. Higher wages may therefore also affect the behavior of the teachers who started working in the school before the introduction of the centralized recruitment drive or the bonuses. To separate this effort margin from the selection effects of the wage bonuses, we compare schools offering higher vs lower bonuses among those that did not have an open teaching vacancy to fill in the 2015 or 2017 recruitment drives. Column (1) shows the RD estimate of the cumulative learning gains for this subsample. The point estimates are very small and statistically insignificant, suggesting that there is no effort response to higher wages for incumbent teachers. In Column (2), we focus instead on the subsample of schools with an open vacancy in 2015 and/or 2017, for either permanent or contract teacher positions. Students in these bonus-eligible schools performed much better in Spanish and math, with effect sizes of 0.3-0.35 standard deviations.

The evidence in Columns (1) and (2) of Table 2 suggests that the recruitment effect of the wage bonus documented in Section 4.3 is the main driver of the observed increase in student test scores. Consistently with the fact that higher wages do not affect the selection of permanent teachers, in Column (3) we document that in schools with open vacancies only

[21] This evidence is consistent with recent findings reported in Agarwal (2017), which document that the primary effect of financial incentives were to increase the quality, not numbers, of medical residents in rural America.

[22] As mentioned in Section 2, the data available does not allow us to precisely match teachers to classes within a school, and hence we are unable to isolate the precise effect of having a better teacher (due to higher wages) in the classroom.

Table 2: Wage Bonus and Student Achievement

Panel A: Dependent Variable is Spanish Test (z-score)				
	No vacancy	Vacancy		
	(1)	(2)	(3)	(4)
		Any vacancy	Permanent teacher	Contract teacher
High Bonus	0.001	0.327	-0.012	0.330
	(0.160)	(0.130)	(0.195)	(0.139)
Mean dep. var. (Low Bonus)	-0.471	-0.469	-0.383	-0.491
Bandwidth	123.388	104.702	173.915	113.922
Schools	368	662	286	615
Observations	3916	9386	3355	8893
Panel B: Dependent Variable is Math Test (z-score)				
	No vacancy	Vacancy		
	(1)	(2)	(3)	(4)
		Any vacancy	Permanent teacher	Contract teacher
High Bonus	0.028	0.378	-0.016	0.483
	(0.177)	(0.144)	(0.249)	(0.160)
Mean dep. var. (Low Bonus)	-0.436	-0.408	-0.296	-0.417
Bandwidth	125.996	108.117	162.799	101.104
Schools	379	691	274	561
Observations	4014	9698	3196	8146

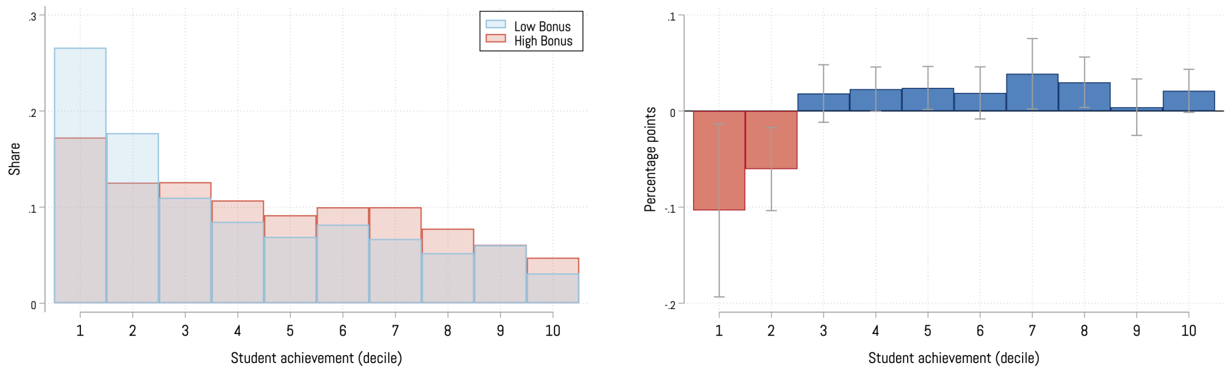
NOTES. This table reports the effect of crossing the population threshold on student achievement in Math and Spanish. In all columns, the outcome variable is the standardized 2018 test scores in Spanish (Panel A) and Math (Panel B) for students in fourth grade. The sample in Columns (1) and (2) is split based on whether the school had an open vacancy (of any type) in the 2015 and/or 2017 centralized recruitment drives. In Column (3) and (4), the sample is further restricted to schools that had vacancies for permanent or contract teachers, respectively. Each cell reports the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom of the table. The table also reports the mean of the dependent variable computed within the interval $(0, +BW)$ (Low Bonus). Standard errors are clustered at the school level.

for permanent teachers the effect of higher wages on student performance is very small and statistically insignificant.[23]

Finally, in Column (4) of Table 2 we consider the subsample of schools with an open vacancy for short-term teaching positions in the 2015 and/or 2017 centralized recruitment drives. Consistently with the substantial increase in the competency level of newly recruited contract teachers, students in schools that receive higher wages perform much better in the Spanish and math achievement tests relative to students in schools that had contract teacher vacancies but were not eligible for the wage bonus. The effect sizes on student performance are very similar to the effect of higher wages on teacher competency scores, as shown in Panel B of Table 1. The magnitudes of the standardized effects reported in Column (4) Table 2 imply an increase of 7% in Spanish scores and of 11% in Math scores, relative to the local

[23]As most of the permanent positions that remain unfilled in the assignment process are later posted as vacancies for a contract teacher (see Section 3.2), the sample that we use in Column (3) of Table 2 excludes schools that, besides having had a vacancy for a permanent position, also had an opening for a short-term position.

Figure 6: Wage Bonus and Composition Effects on Student Achievement



a. Shares at Population Cutoff **b. RD Estimates**

Notes. Panel A reports the relative shares of students by decile of the distribution of the average score in Spanish and math, separately for schools located to the right (Low Bonus) and left (High Bonus) of the population cutoff. Bars and vertical lines depicted in Panel B indicates the corresponding bias-corrected regression-discontinuity estimates of crossing the population threshold and the associated confidence intervals at the 90% level (Calonico et al., 2014). The sample includes schools with an open position for contract teachers.

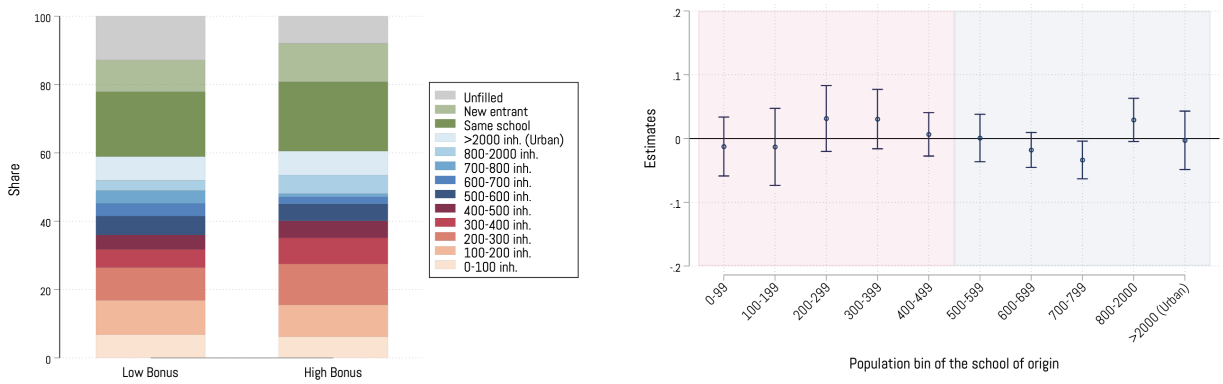
averages (in levels) at the right-hand side of the population cutoff (low bonus).

We further explore the relative effects of the recruitment of a more competent teacher along the test score distribution. Panel A in Figure 6 displays the relative shares computed at both sides of the population threshold by the deciles of the average score in Spanish and math. Higher wages have a more pronounced effect on reducing the proportion of students who score in the the first two deciles of the test score distribution, while the effects are smaller in magnitude and relatively uniform for better-performing students. In Panel B of Figure 6 we confirm these asymmetric match effects between the newly-assigned teachers and students using the deciles of the average score as dependent variables in separate RD regressions.

4.5 Additional Evidence

One potential concern with the identification of our main estimates is that the observed threshold-crossing effect could possibly violate SUTVA, whereby high-quality teachers who end up choosing a school in a locality with slightly less than 500 inhabitants would have otherwise chosen a school in a somewhat more populated locality. While a priori this may be an issue, we argue that it is not warranted in our setting. First, it is important to remark that differently sized localities are not necessarily geographically close to one another. In fact the median geodesic distances between the three closest below-cutoff schools and the schools just above the cutoff for the sample of contract teachers are approximately 10km,

Figure 7: Wage Bonus and the Origin of Newly Recruited Teachers



a. Shares at Population Cutoff **b. RD Estimates**

Notes. Panel A displays the relative shares (computed at the population cutoff) of the contract teachers who are assigned through the assignment mechanism based on the location of the previous schools recorded in the teacher occupation and payroll system (*NEXUS*), separately for schools located to the right (Low Bonus) and left (High Bonus) of the population cutoff. Panel B reports the effect of crossing the population threshold on the probability that the vacancy is filled by a teacher whose previous location falls into the population bin indicated in the x-axis. The sample includes all contract teacher vacancies assigned to a certified teacher in the 2015 and 2017 processes. Bars report the bias-corrected regression-discontinuity estimates along with confidence intervals at the 90% level obtained using the robust estimator proposed in Calonico et al. (2014).

20km, and 30Km, respectively (see Figure A.5 for the full distribution).

Second, Panel A in Figure 7 shows the relative shares of the assigned applicants at both sides of the population threshold by the size of the localities of the schools where they were previously teaching (if any). The share of teachers who were working in a school located just above the 500-inhabitant population cutoff is small (4-5%) and it does not seem to vary between schools that are eligible for a high bonus and a low bonus. The estimates displayed in Panel B of Figure 7 confirms this visual pattern, showing fairly precise zero sorting effects for teachers who were previously working in schools located around the population cutoff (i.e. the 400-500 and the 500-600 population bins).

Third, in the next Section we estimate teacher preferences over wages and job attributes in order to properly construct counterfactual assignments in the absence of the wage bonus policy. We show in Figure C.2 simulation-based evidence that is inconsistent with potential SUTVA violations around the population cutoff that determines eligibility to the higher wage bonus (see Section 5.4).

Increased competition for vacant positions can lead to an increase in the quality of applicants who select into higher-paying teaching jobs either by selecting a larger pool of prospective teachers into the public sector or by reallocating existing competent teachers from urban or other rural schools toward *Extremely Rural* locations. To show that the selection margin is active in our context, and hence that the results are not entirely driven

Table 3: Wage Bonus and the Selection of New Entrant Teachers

	All	Age		Private sector experience	
	(1)	(2)	(3)	(4)	(5)
		<30	≥30	Yes	No
High Bonus	0.047	0.041	0.004	0.051	-0.003
	(0.037)	(0.017)	(0.031)	(0.028)	(0.025)
Mean dep. var. (Low Bonus)	0.156	0.032	0.126	0.092	0.065
Bandwidth	140.335	160.224	160.479	137.804	165.653
Schools	805	943	943	789	979
Observations	1927	2215	2215	1894	2289

NOTES. This table reports the effect of crossing the population threshold on the selection of new entrant teachers. In Column (1), the outcome variable is a binary indicator for whether the vacancy is filled by a teacher who was not previously teaching in any public school (new entrant teacher). In Columns (2) to (5), the outcome variable is the interaction between the new entrant indicator and a set of additional characteristics of the assigned teacher. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the interval $(-BW, 0]$ (left-hand-side of the cutoff). Standard errors are clustered at the school×year level.

by teachers sorting within the public education system, we focus on the subset of applicants who were not previously teaching in any public school. As mentioned above, these new entrants in the system represent a non trivial share of the assigned applicants who earn a position as contract teacher in our data. In Table 3 we show RD estimates on the pure selection effect of a higher wage bonus for the new entrants in the public sector, which is relatively large and positive (but noisy). This effect can be explained by a large and more precisely estimated inflow of recent graduates (column 2) as well as by applicants who had prior teaching experience in private schools (column 4).

Overall, the evidence suggests that the effect of the wage bonus on teachers' sorting patterns is not merely a zero-sum game. We reconsider this issue in Section 6.1 in the context of the estimated model of teacher preferences (see Figures 12-13). These findings provide further support for the notion that positive net inflows from the outside option partly explain the overall reallocation patterns induced by the current system of wage bonuses.

We conclude this Section by ruling out alternative mechanisms through which the wage bonus may affect student outcomes. For example, wage bonuses could affect student achievement by changing the size and composition of the teaching staff. However, Table B.6 shows that the wage reform has small and statistically insignificant effects on the number of teachers, the relative share of permanent and contract teachers, and student-to-teacher ratios. Alternatively, teachers may be more likely to stay in their jobs for longer periods in the presence of the wage bonus, although Table B.7 shows that wage bonuses do not affect retention rates during the study period.[24]

Taken together with the results shown in Table 2, this evidence strongly suggests that the inflow of more competent teachers mostly explains the large improvements in learning outcomes for the students enrolled in higher-bonus schools. While there may be an effort margin due to the wage incentives for the newly recruited teachers, the evidence reported in Table B.8 documents little if no composition effects along teachers' observable characteristics. This seems to suggest that selection based on unobserved traits such as intrinsic or extrinsic motivation is unlikely to operate in this setting.

5 An Empirical Model of Teacher Preferences

5.1 Utility and Preferences

Following the discrete choice literature, we specify an empirical model of teachers' preferences that flexibly capture substitution patterns between school or local amenities and the compensation offered at every specific job postings throughout the country. We model the (indirect) utility that teacher i gets from being matched with school j as:

$$v_{ij} = \alpha_i w_j + \boldsymbol{\beta}_i' \boldsymbol{z}_j + \boldsymbol{\delta}' \boldsymbol{d}_{ij} + \boldsymbol{\lambda}' \boldsymbol{m}_{ij} + \epsilon_{ij}, \tag{2}$$

where w_j is the wage posted at school j in thousands of Peruvian Soles and $\boldsymbol{z}_j$ is a vector of locality and schools' characteristics that generate variation in teachers' utility across job postings. The vector $\boldsymbol{z}_j$ contains a poverty index, an infrastructure score at the locality level capturing the overall level of amenities associated to a given area, a polynomial in the population of the locality of the school and the time-to-travel (in hours) between the locality of the school and the province's capital.[25] It also includes a set of indicator variables for whether a given school belongs to specific regimes that determine eligibility for other wage bonuses such as multi-grade, single-teacher, bilingual, and/or to the specific geographic areas (see Figure A.3).

We account for the fact that individual-specific factors may affect the extent to which teachers' labor supply vary with respect to wages and other school or locality characteristics. For example, men may be more sensitive to wages than women due to gender norms and/or

[24] The effect on retention rates between academic years is partly mechanical, since these are temporary positions with a duration of one or two years.

[25] The poverty index is an asset-based measure of poverty at the individual level (poverty score) computed by the Ministry of Economy and Finance that we aggregate at the locality level. The infrastructure score collapses a set of indicators measuring infrastructure quality at the locality level through a multiple correspondence analysis (see Panel D of Table A.2).

gender differences in outside options. Similarly, teachers at an early stage of their professional life may be more or less sensitive to wages and other local amenities due to life cycle considerations or career concerns. We flexibly capture such patterns through the vectors α_i and $\boldsymbol{\beta}_i$, which are defined as:

$$\boldsymbol{\beta}_i = \boldsymbol{\gamma}_0 + \Gamma_1 \boldsymbol{x_i},$$
$$\alpha_i = \alpha_0 + \boldsymbol{\alpha_1'} \boldsymbol{x}_i + \sigma \nu_i,$$

where $\boldsymbol{x}_i$ is a vector of indicator variables for teacher characteristics, such as gender, experience, residential location, and competency and Γ_1 is a matrix of coefficients, which is conformable with $\boldsymbol{x_i}$ and $\boldsymbol{z}_j$. We also include ν_i, a log-normally distributed random coefficient capturing unobserved preference heterogeneity for wages which would not be accounted for by $\boldsymbol{x}_i$. The presence of heterogenous preferences in our model generates flexible substitution patterns between wages and other school and locality characteristics that are key to interpreting the role of the wage schedule as well as school and locality amenities in the counterfactual analysis that we present in Section 6.

In addition to the fairly rich structure of preferences for the different school-level factors specified above, the discrete choice model described by equation (2) features two different sources of match-specific preference heterogeneity. Moving costs and other costs associated to switching jobs are captured by $\boldsymbol{d}_{ij}$, a vector of linear splines in the geodesic distance between the location of school j and teacher i, as measured by the location of the school where this teacher was working in the previous academic year. For novice teachers we use the location of the university/institute from which they recently graduated. For the remaining non-novice teachers with no prior experience in the public sector (new entrants) we use the locality of residence in 2013. Alternatively, $\boldsymbol{d}_{ij}$ may also reflect the fact that applicants may not be aware of all the available positions across the entire country and/or of their specific attributes—especially those far away from their location (see Panel B of Table A.4). In this case, the parameter vector $\boldsymbol{\delta}$ should be interpreted as a combination of moving/switching costs as well as the probability that a given job posting lies within teacher i's consideration set.

The vector $\boldsymbol{m}_{ij}$ contains ethnolinguistic match effects, indicating whether teacher i's indigenous native language (if any) and school j's secondary language of instruction (if any) coincide. These capture language barriers that teachers might face when working in a school from a different ethnolinguistic group and, more broadly, any specific taste for living in a community with shared cultural traits. In settings with rich ethnolinguistic diversity, such as in Peru, these type of match effects may be particular relevant to characterize the current population of applicants (see Section 2). To avoid sparseness in the data, beyond the two most prominent ethnolinguistic groups (*Quechua* and *Aymara*) we consider the two most popular and well-defined indigenous groups of the Amazonian regions, the *Ashaninka* and *Awajun*, and lump together all the remaining minorities into one residual category.

All residual unobserved tastes of teacher i for school j are captured in the ϵ_{ij} term that is assumed to be distributed *iid* across i and j through a Gumbel distribution with normalized scale and location. Finally, we include all private schools that are not part of the centralized assignment mechanism or any other labor market opportunity not observed in the data as being part of the outside option.

We specify the utility of the outside option as:

$$v_{i0} = \boldsymbol{\eta}_0 + \boldsymbol{\eta}_1' \boldsymbol{q}_i + \epsilon_{i0}, \tag{3}$$

where $\boldsymbol{q}_i$ is a rich set of characteristics for teacher i. These characteristics include gender, experience in both the public and the private sector, ethnicity, the competency score, the population of the place of residence, and the time-to-travel between the provincial capital and the place of residence.

5.2 Identification and Estimation

We observe data on teachers' choices over job postings from two sources. The first data source is the rank-ordered lists of applications for permanent positions. The second source of information is the realized match for short-term positions given teachers' competency scores and choice of school district. We choose to estimate the discrete choice model presented in the previous subsection using exclusively the second source of information for several reasons. First, the vast majority of applicants are not eligible for a long-term position and among the 10% of teachers that do qualify, half either reject all offers or do not get any and eventually participate in the assignment mechanism for short-term positions (see Table A.1). Second, and perhaps more importantly given our previous finding that wage bonuses do not affect the sorting outcomes of permanent teachers, studying the behavior of this sub-population becomes less relevant for the purpose of the optimal targeting of wage bonuses aimed at reducing inequalities in the allocation of public-sector teachers in Perú. Finally, the design of the assignment mechanism for permanent positions gives rise to incentives for teachers not to report their preferences truthfully in the submitted rank-order lists. Our survey elicits preferences over job postings that are unconditional on the institutional constraints of the application system. Almost one third of the surveyed teachers do not apply to their most preferred school, which clearly indicates the presence of strategic considerations in our setting (see Table A.4). Learning about teachers' preferences from the available data on the rank-ordered lists would require more involved methods and additional data that go beyond the scope of this paper.[26]

None of these issues arise when focusing on contract teachers. Recall from Section 3.2 that within each administrative unit (school district), contract teachers are ranked based on their competency score and are sequentially assigned to their preferred school among the options that still have open vacancies. This procedure is iterated until all vacancies are filled and/or all teachers are assigned. Given the structure of the assignment mechanism, we assume that the realized matching equilibrium is stable, meaning that teachers would not be accepted by a school that they strictly prefer with respect to their current match. The assignment mechanism, indeed, directly implies that the match is stable within each school district. Overall stability might be compromised if teachers do not correctly predict in which school district their preferred feasible school is located. However, the presence of an aftermarket that assigns the remaining unfilled vacancies mitigates these concerns.

Stability implies that the observed match between schools and teachers can be interpreted as the outcome of a discrete choice model with individual-specific choice sets that depend only on teachers' competency scores (Fack et al., 2019). Under the distributional assumptions stated in Section 5.1, we can thus write the following log-likelihood function for the n teachers who apply to short-term positions through the centralized application system:

$$L(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n} \log \left\{ \int_0^\infty \left(\frac{\exp \tilde{v}_{i\mu(i)}}{\sum_{k\in\Omega(s_i)\cup\{0\}} \exp \tilde{v}_{ik}} \right) dF(\nu_i) \right\}, \tag{4}$$

where $\mu(i)$ is the school assignment of each teacher i, $\Omega(s_i)$ is the feasible choice set, which depends on teacher i's competency score s_i, and $\tilde{v}_{ij}$ is the deterministic component of the indirect utility function in (2). The term inside the brackets of equation (4) is the conditional probability that teacher i chooses school j from her feasible choice set, which is also a function of the cumulative distribution function of the log normal distribution, $F(\cdot)$. We compute the integral in (4) numerically using a Gaussian-Hermite quadrature (Judd, 1998).

In this model, preference parameters $\boldsymbol{\theta}$ are identified if (i) the observable characteristics $(w_j, \boldsymbol{z_j}, \boldsymbol{d_{ij}}, \boldsymbol{m_{ij}}, \boldsymbol{x_i}, \boldsymbol{q_i})$ are independent of both taste shifters ϵ_{ij} and the random coefficient

[26] Beyond a model of supply and demand, the complex nature of the assignment process would require taking into account that teachers might have biased beliefs regarding their admission chances (Kapor et al., 2020), which we don't observe in our data. It would also be important to carefully model the dynamic incentives between permanent positions and short-term positions that necessarily arise due to the sequential nature of the assignment mechanism. This extension is outside of the scope of the current project and is left for future research.

ν_i and (ii) the feasible choice sets $\Omega(s_i)$ are independent from the taste shifters ϵ_{ij} conditional on observables. The first assumption implies that the set of observables has to be rich enough such that residual preference heterogeneity can be modeled as an exogenous shock. This might be problematic if, for instance, we believe that we are omitting a set of relevant variables that would be correlated with wages.[27] However, given that wages are set exogenously via deterministic rules and that we are controlling flexibly for all relevant wage determinants, we are confident that this assumption is reasonable in our setting. The second condition may not hold if there is a possibility that the decision by teacher i to accept or reject a given job posting may trigger a chain of acceptance or rejections by other teachers that may feed back into teacher i's set of feasible schools (Menzel, 2015). Preference cycles of this sort are ruled out in our setting, since schools rank applicants according to the same criterion (i.e. the competency score). Another potential concern that may arise in this setting is that some schools of a specific type $\boldsymbol{z_j}$ may be unreachable to low scoring teachers. To mitigate these concerns and restore full support, as a proxy for teacher quality in the model, we include in the $\boldsymbol{x_i}$ vector a discrete measure of curricular and pedagogical knowledge, instead of the total competency score that determines priorities in the system (see Section 3.1).

5.3 Estimation Results

Panel A of Table 4 reports selected preference estimates for relevant school and locality characteristics such as wages, poverty, infrastructure, and indicators for whether a school is multigrade or single teacher. The full set of estimated parameters of the model described in Equation (2) is presented in Table C.1. The estimated preferences for wages (α_i) are heterogeneous along both observed and unobserved dimensions. For example, male applicants are much more responsive to compensations than females. Applicants living in urban areas and more competent teachers are also more sensitive to changes in wages, which is consistent with the fact that living in cities is more expensive and that ability and/or effort are likely to determine wage sensitivity. We do not find any significant heterogeneity with respect to teaching experience in the public-sector, suggesting that many different channels may be at play that are potentially cancelling each other out. For instance, career concerns for novice teachers may push down the wage coefficient while at the same time life-cycle considerations are consistent with a positive correlation between experience and the sensitivity to the wage

[27] In the context of the centralized matching between residents and hospitals in the US, Agarwal (2015) employs a control function approach to deal with the potential endogeneity between salaries and unobserved program characteristics. The approach relies on the availability of an instrument that is excludable from the preferences of the residents.

Table 4: Model Estimates – Selected Parameters

Panel A: Wage (α) and School/Locality Characteristics ($\boldsymbol{\beta}$)										
	Wage		Poverty Score		Infrastructure		Multigrade		Single Teacher	
	0.815	(0.120)	-0.201	(0.035)	-0.054	(0.054)	-0.237	(0.119)	-0.786	(0.192)
× Male	0.611	(0.157)	0.115	(0.032)	-0.060	(0.048)	0.019	(0.099)	0.519	(0.137)
× Experience ≥ 4 yrs	0.070	(0.053)	0.097	(0.036)	0.132	(0.052)	-0.284	(0.118)	0.020	(0.181)
× Urban	0.115	(0.061)	-0.060	(0.044)	0.036	(0.068)	0.009	(0.170)	-0.125	(0.242)
× Competent	0.170	(0.067)	-0.065	(0.047)	0.198	(0.076)	-0.782	(0.185)	-0.752	(0.351)
Std. Deviation (σ)	0.560	(0.053)								

Panel B: Teacher-School Match Effects					
	Ethnolinguistic Match ($\boldsymbol{\lambda}$)		Switching/moving Costs ($\boldsymbol{\delta}$)		
Quechua × Quechua	1.488	(0.158)	Distance < 20km	-0.187	(0.003)
Aymara × Aymara	1.375	(0.537)	20km < Distance < 100km	-0.033	(0.001)
Ashaninka × Ashaninka	2.243	(0.558)	100km < Distance < 200km	-0.018	(0.001)
Awajun × Awajun	2.086	(1.020)	200km < Distance < 300km	-0.017	(0.002)
Other × Other	0.995	(0.113)	Distance > 300km	-0.002	(0.000)

Notes. This table displays selected estimates and standard errors (in parentheses) of the parameters of the model described in Equation (2). Panel A shows the estimated coefficients associated to a selected set of schools/locality characteristics while Panel B shows estimated preferences for geographical proximity as well as the interaction between schools' language of instruction and teachers' own native language. The data used contains choices of the pool of 59,949 applicants (note that 500 applicants are left out due to missing data) that participated in the allocation of short-term contracts for public primary schools in 2015. Estimates are obtained by maximizing the likelihood described in Equation (4) where the integral is computed numerically in an inner loop via a Gaussian-Hermite quadrature. Table C.1 displays the full set of the estimated coefficients.

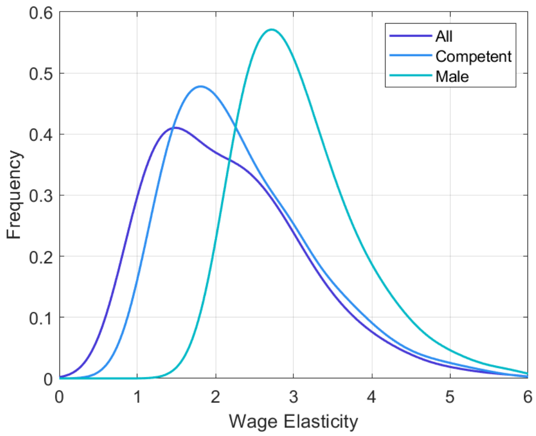
posted in a given location.

The large and significant standard deviation of the random coefficient ν_i displayed in Panel A of Table 4 indicates the presence of substantial unobserved taste heterogeneity with respect to wages that is not explained by the observed teacher characteristics included in the model. Figure 8 displays the wage elasticities implied by the estimates of the model. These estimates combine both observed and unobserved sources of preference heterogeneity with respect to the wages posted at each vacancy, and they range from close to 0 to around 6, with a global average of 2.19. Several interesting patterns emerge from these distributions. For instance, increasing wages seems to be a more prominent "pull" factor for attracting teachers in rural schools than in urban schools. This result highlights the trade-off between amenities, which are more scarce in rural areas, and wages, implying that wages enter more prominently into teachers' compensating differentials.

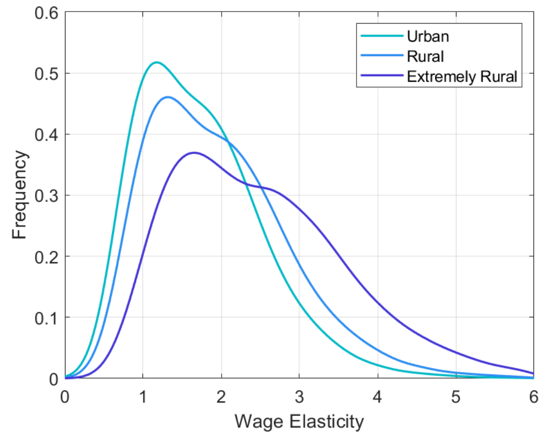
Preference estimates for other job characteristics ($\boldsymbol{\beta}_i$) are also displayed in Panel A of Table 4. The estimates show that on average teachers have a strong distaste for localities with high levels of poverty, for schools that are multigrade, or those with a single teacher. These patterns are more evident among competent and more experienced teachers, which suggests that complementary policies aiming at broadly improving school and locality infrastructures may be effective at reducing spatial inequalities in the allocation of public-sector teachers.

Panel B of Table 4 displays the ethnolinguistic match effects and the effect of the geodesic distance between teachers and schools. The magnitudes of the estimated parameters show

Figure 8: Wage Elasticities



a) Teacher Characteristics



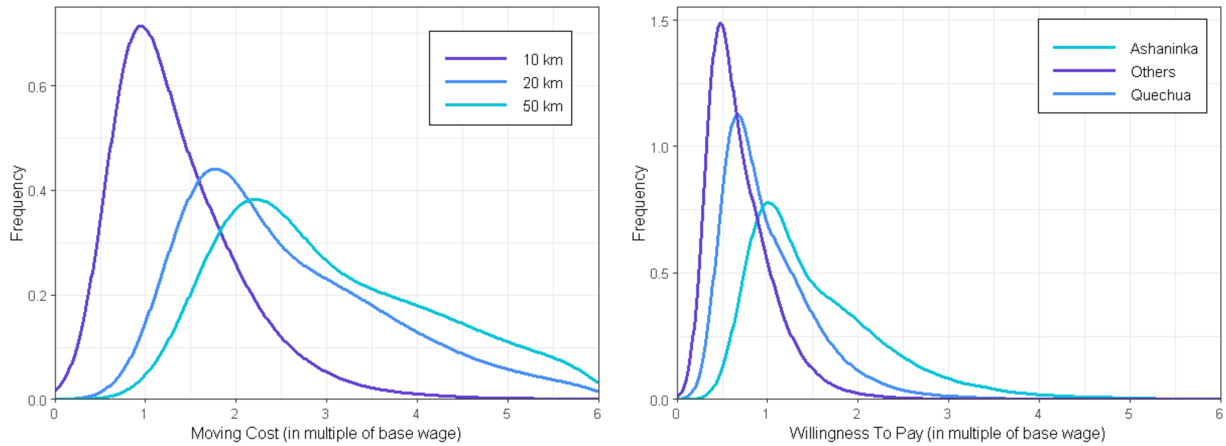
b) School Characteristics

NOTES. This figure depicts the distribution of the wage elasticities which are computed using the estimates from Table 4. These elasticities give the % change in the conditional probability that teacher i chooses school j, which we denote P_{ij}, resulting from a 1% increase in the wage proposed in school j: $\frac{\partial P_{ij}}{\partial w_j}\frac{w_j}{P_{ij}} = \alpha_i w_j(1 - P_{ij})$. Panel A plots the distribution of this elasticity for different groups of teachers (all, competent, and male), while Panel B displays heterogeneity of this distribution with respect to the rurality of schools' locality.

that both play a very important role in teachers' choices over schools. Figure 9 documents heterogeneity across applicants in terms of the implied wages needed to compensate teachers from moving farther away from where they live (Panel A) as well as their willingness to pay for being assigned to a school offering a bilingual education that corresponds to the own ethnolinguistic group (Panel B). Moving costs are estimated to be substantial in our context. It would take on average 2.75 times the current base wage to make teachers willing to move 50km. away from where they currently live.[28] Similarly, the average teacher who speaks a native language would be willing to pay up to the amount of the base wage in order to teach in a school from her own ethnolinguistic group, with higher willingness-to-pay for the minority groups such as Ashaninka or Awajun. To the extent that these minorities are mostly located in rural areas with school vacancies that are in excess demand for bilingual teachers, place-based policies aimed at leveraging these strong match-specific effects (both ethnic and geographic) might be a promising alternative to wage incentives as a way to enhance the local supply of teachers.

[28] As mentioned in Section 5.1, the estimated preference parameters for distance may also capture applicants' limited awareness about job postings that are located farther away from their current locations. Overall, the high sensitivity to distance found here is consistent with recent evidence that draws directly from the rank-ordered lists of permanent teachers in Perú (Bertoni et al., 2019).

Figure 9: Match Effects



a) Moving Costs **b) Willingness to Pay**

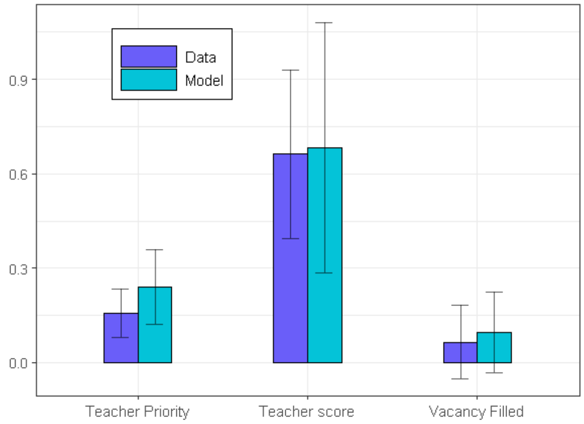
NOTES. Panel A plots the estimated distributions of the cost incurred by teachers when moving away from their previous location by 10km, 20km and 50km, respectively. These figures are computed using the estimates of the distance spline coefficients and the random coefficient on wages displayed in Table 4. Panel B plots the estimated distributions of the willingness to pay (in multiple of the base wage) for indigenous teachers to get assigned to (bilingual) schools with secondary language of instruction that is the same as their own language.

5.4 Model Validation

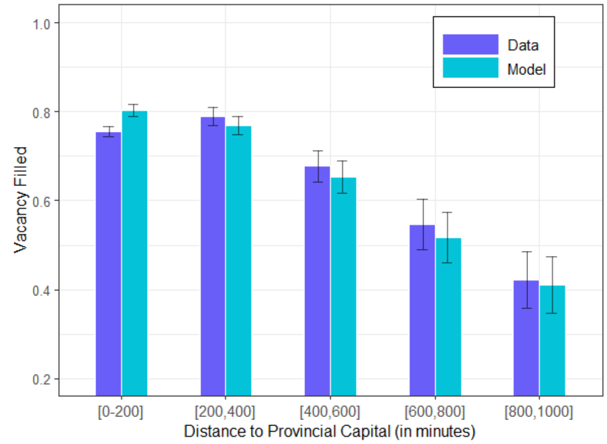
In this subsection we assess the validity of our model by evaluating how well its estimated parameters predict some key moments in the data. In particular, it is important to test the empirical plausibility of the estimated wage elasticities from Figure 8, given that the counterfactual analysis in Section 6 will mainly rely on those preference parameters. To do so, we verify the consistency between the sorting patterns predicted by the model and the estimated effects at the 500-inhabitant population threshold for eligibility of the rural bonus discussed in Section 4. The predicted size of the effects in teacher sorting outcomes can be used for model validation since its magnitude would be entirely explained by the estimated wage elasticity. We thus simulate teachers' choices using the estimated preference parameters, replicate the RD analysis on simulated data, and compare the resulting estimates with those obtained with the actual data. In addition, we assess the overall fit of the model in terms of the global sorting patterns by the degree of remoteness of the localities where schools are situated.

Figure 10 shows the corresponding estimates of this exercise along with the associated 95% confidence intervals. The evidence reported in Panel A documents that the estimated model seems to predict very well the different sorting patterns as induced by the wage bonuses that we observe in the data. This validation exercise alleviates concerns about the

Figure 10: Comparing RD Estimates, Observed Sorting and Simulated Data



a) Threshold Crossing Effects (pop.=500)



b) Share of Filled Vacancies by Remoteness

Notes. Panel A in this figure shows the estimated RD jump in vacancy filled, teacher score and the teacher priority index at the 500 locality population threshold both in the actual data and in the simulated data. The simulated assignment is generated by running the serial dictatorship algorithm using predicted utilities computed from the estimates of Table 4 as well as a randomly drawn set of taste shocks ϵ_{ij}. Panel B compares the share of vacancies filled in the actual data and in the simulated data depending on how far the schools posting the vacancies are located from the provincial capital.

potential correlation between wages and unobserved school characteristics (see Section 5.2). This is even more reassuring given that the rural bonus policy explains only a small portion (less than 10%) of the total variation in wages across job postings that is used to identify the wage coefficient in the choice model. The evidence shown in Panel B further confirms that our model precisely replicates the negative gradient between the proximity of the locality to the provincial capital and the share of filled vacancies. We provide additional measures of model fit in Figure C.1.

We finally use the estimated model to provide supporting evidence for the RD analysis. More precisely, we use the model to evaluate whether the concerns about a possible violation of SUTVA, i.e., the possibility that high-quality teachers who sort into bonus-eligible schools would have chosen schools just above the population thresholds in the absence of the bonus, are warranted in our setting. We do this by simulating a counterfactual assignment with no rural wage bonuses and compare the resulting sorting patterns with the status quo scenario (i.e., with bonuses). Figure C.2 shows RD charts based on these simulations. We find no systematic differences in teacher competency scores at the cutoff under the no-rural-bonus regime (Panel A), as expected. The introduction of bonuses at the 500-inhabitants threshold (Panel B) generates a discrete jump in teacher quality, which is comparable to the results in Panel D of Figure 4. More importantly, the intercepts and the slopes of the interpolating lines above the cutoff, that is, for schools in the low-bonus regime are virtually identical under the counterfactual and the status-quo regimes. This evidence is fully consistent with SUTVA.

6 Counterfactual Analysis

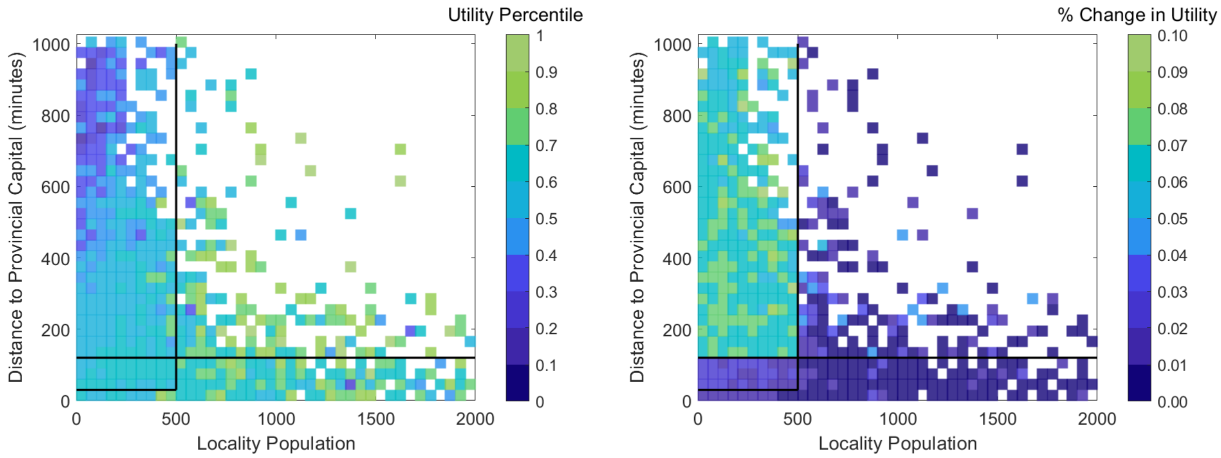
6.1 Evaluation of the Actual Wage Policy

Public-sector teachers who work in schools with a specific set of locality and school characteristics receive additional compensations that vary between 4% and 36% of the base wage (see Figure A.3). The rural wage bonuses studied in Section 4 are part of this larger incentive scheme. We use the estimated preference parameters from the model in the previous Section to evaluate the effects of the overall system of wage bonuses currently in place for the universe of public sector teachers in Perú. Unlike the estimates discussed in Section 4, the structure of the model allows us to evaluate the policy effects away from the RD threshold, thus gaining a broader perspective on the equilibrium effects of wage bonuses on teacher sorting.

In order to generate our counterfactual of interest, we first run the serial dictatorship algorithm in which teachers are assigned to short-term positions using their estimated preferences but in the absence of any wage bonuses (including the rurality bonuses).[29] Panel A in Figure 11 plots the percentile of desirability, as measured by local averages in the median utility predicted by the model without any wage bonus in each school. The model estimates imply that we would need to offer the average teacher a wage that is 3.5 times higher than the base wage in order to make her indifferent between a school located in the first and in the last percentiles of desirability. The desirability index monotonically decreases with the distance to the provincial capital whereas it is only weakly correlated with the population of the locality. Schools located close to the cutoffs for eligibility to the rural bonus are not the least desirable, suggesting that some (if not most) of the effect of the wage bonus may actually show up more prominently in localities that are away from these cutoffs. This is confirmed by Panel B, which displays the cell-averages of the percentage changes in predicted utility between the status-quo (which include all the wage bonuses) and the "no bonus" counterfactual from Panel A. Changes in utility are heterogenous within the *Extremely rural* category, indicating large differences in the initial conditions of the schools that receive the

[29]The school-specific and locality-specific determinants of the other wage bonuses are highly correlated with both dimensions of rurality (distance to provincial capital and population). Figures C.3-C.4 separately show the impacts of the other wage bonuses (vis-a-vis the no-bonus scenario) and those of the rural bonus (vis-a-vis the other-bonus scenario) along the support of the univariate distributions of population and the time-to-travel to the provincial capital. The results suggest that the bulk of the policy effects on sorting outcomes are almost entirely driven by the rurality bonus.

Figure 11: Fitted Teacher Utility



a) No Bonus **b) Wage Bonus**

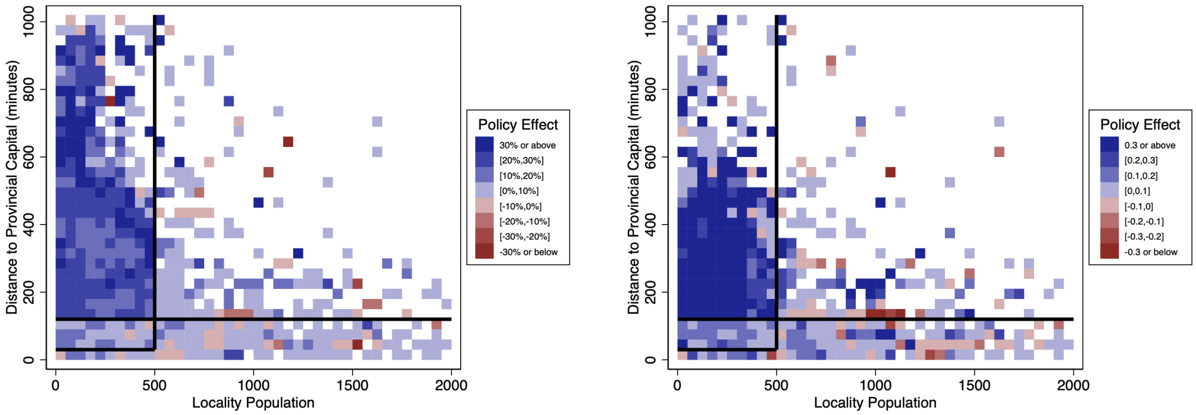
NOTES. Panel A plots the average percentiles of the median predicted utility associated with each vacancy from the estimates reported in Table C.1 for a fine grid in the population and distance to provincial capital space (each cell is 50×30). Panel B reports the average percentage changes in the median utility between the status quo and the counterfactual scenario with no wage bonuses.

same S/ 500 rural bonus.

We next use the estimated preferences to simulate the allocation of teachers into schools under the counterfactual scenario where we remove all wage bonuses and compare it to the allocation obtained under the status quo with the system of wage bonuses actually in place. While the first two columns of Table 5 document some aggregate patterns related to each of these two assignments, in Figure 12 we display the spatially disaggregated differences between the actual wage bonus policy and the no bonus scenario. Each cell in the figure is defined by discrete values of population and time-to-travel. Most of the positive effects of the wage-incentive policy manifest in schools in localities with less than 500 inhabitants and that are farther than 120 minutes away from provincial capitals, which is due to the targeting and the magnitudes of the rural bonus. Consistently with the evidence reported in Section 4, the effects are not symmetric for the two sorting outcomes. Panel A shows that wage bonuses achieve a higher proportion of filled vacancies. These effects are relatively small and they do not vary systematically across the population threshold associated with the eligibility of the rural bonus, as shown by the vertical line in the figure. Indeed, the effects of the wage bonus appear more pronounced in very remote schools (i.e., in the upper left corner of Figure 12). Panel B instead shows larger effect sizes, with most of the effect on teacher quality that is concentrated in schools just below the population cutoff and near the time-to-travel cutoff where the data is more concentrated (see Figure 3)

Importantly, our results further show that the effects of the wage bonus policy are positive

Figure 12: Policy Effects on Teacher Sorting

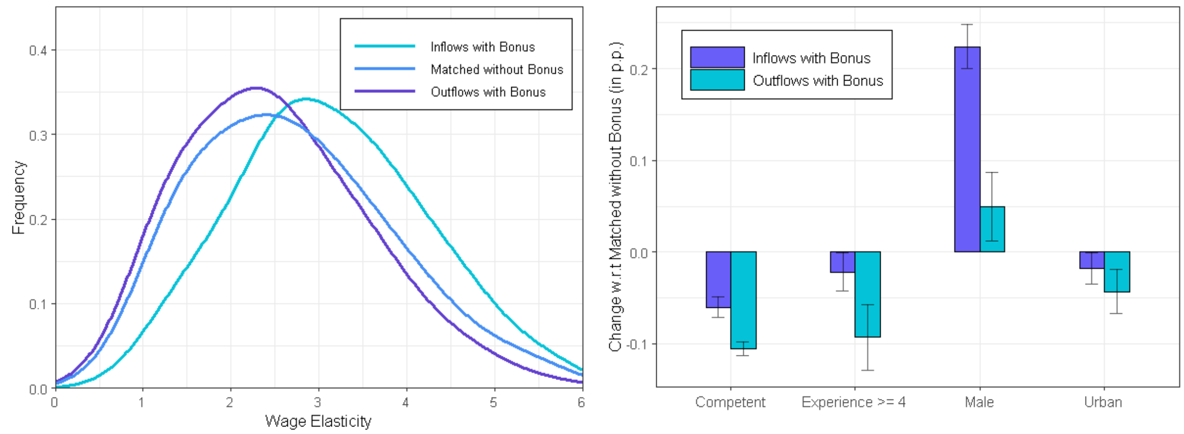


a) Share of Filled Vacancies **b) Teacher Competency Score**

Notes. This Figure uses simulated assignment data computed by running the serial dictatorship algorithm with predicted utilities using the estimates from Table 4 as well as a randomly drawn set of taste shocks ϵ_{ij}. For each outcome variable, we compute kernel-weighted averages in the population and distance to provincial capital between the assignment simulated under the actual policy and a counterfactual scenario with no wage bonuses.

across most of the support of the population and time-to-travel variables, alleviating the concern that the compensation policy generates a zero-sum reallocation. This is explained by the inflow (outflow) of teachers from (to) the outside option. We document these composition effects in Figure 13. Panel A compares the empirical density of the wage elasticity for assigned teachers under the no-bonus scenario with the corresponding distributions for those who choose a position under the actual system of wage bonuses and who would have otherwise (i.e. without bonuses) chosen the outside option, and for those who choose the outside option with the wage bonuses and would have otherwise been matched to a school vacancy in the absence of bonuses. As expected, the distribution of the wage elasticity for applicants who are drawn into short-term teaching jobs first-order stochastically dominates the distribution of the applicants who are displaced and/or pushed toward the outside option due to the wage incentives (p-value$<$0.001). Panel B displays the average percentage changes in selected characteristics between the two sub-populations of teachers who enter and exit as a result of the wage incentives with respect to the average levels of those who are matched without wage bonuses. The *Inflows with Bonus* are disproportionally more likely to be male, which is consistent with the higher wage elasticity of this sub-group of applicants shown in Figure 8. They are also less competent (based on the discrete measure of curricular and pedagogical knowledge used in the model) and less experienced, when compared to the pool of existing teachers. Instead, when compared to the *Outflows with Bonus*, they are (slightly) more competent and more experienced.

Figure 13: The Effect of the Wage Bonus on the Selection of Teachers



a) Distributions of Wage Elasticity **b) % Change in Teacher Characteristics**

Notes. Panel A of this Figure plots the empirical PDFs of the wage elasticity for the assigned teachers in the counterfactual scenario without any wage bonuses, along with (i) the *Inflows with Bonus* which are pulled out from the outside option thanks to the wage bonus policy and (ii) the *Outflows with Bonus* which are crowded out to the outside option because of the wage bonus policy. Panel B plots the percentage change in the average characteristics of the individuals belonging to these two groups with respect the assigned teachers under the no-bonus scenario.

6.2 Alternative Wage Policies

The evidence in Section 4.4 shows that policies that incentivize teachers sorting toward disadvantaged areas can increase efficiency along with equity given that competent teachers are more effective on low achieving students. In the last part of our analysis, we investigate whether we can achieve a more equitable allocation of teachers by redesigning the wage bonus policy. We focus on two independent policy goals that target either the extensive or the intensive margin of teachers' sorting outcomes, as discussed in Section 6.1. Objective (i) is having at least one filled vacancy in each school. Objective (ii) is to recruit at least one high-quality (i.e., above the median teacher in urban areas) teacher in each school.[30] Policy objective (i) and (ii) are equivalent, the only difference being that the set of applicants considered is not the same. The aim of this exercise is to determine what would be the cheapest wage bonus policy that achieves either objective (i) or (ii) *under the actual assignment mechanism in place* for contract teachers.

We consider a counterfactual economy where schools are allowed to propose different wages to teachers (Kelso and Crawford, 1982; Hatfield and Milgrom, 2005). We restrict the

[30] This threshold implies that objective (ii) mimics the size of the estimated effects of the wage bonus policy on teacher competency scores reported in Section 4.3—i.e. 0.45 standard deviations above the overall sample mean.

pool of available applicants to the set of high quality teachers under policy objective (ii).[31] To be consistent with the institutional framework, we impose that schools have to pay the same wage to all the teachers they hire. We then use the estimated preference parameters from Section 5 in order to infer how teachers rank each school-wage allocation, and we embed the policy objectives defined above into schools' preferences over each possible allocation through the following two assumptions:

(A1) For a fixed wage, we assume that schools have the same preferences as in the actual assignment mechanism. Teachers are individually ranked by test scores and the most preferred group of q teachers is the one composed of the q best scoring teachers.[32] Schools cannot leave a vacancy empty if a teacher would be willing to fill it at that wage.

(A2) We assume that schools have lexicographic preferences when ranking two allocations with different wages. Keeping all slots empty is dominated by any other allocation at any given wage. Otherwise, schools will always prefer the allocation with the lowest wage.

These preferences satisfy the substitute condition. The proof is provided in Appendix D.1. We thus leverage the seminal result in Hatfield and Milgrom (2005) that shows that a stable set of contracts always exists in the proposed mechanism. There exists an allocation such that there is no school-teacher pair that would prefer to break their match and rematch together under any proposed wage. These stable contracts form a lattice where the largest and smallest elements are the school-optimal stable allocation and the teacher-optimal stable allocation, respectively. We can either use the school-proposing generalized DA algorithm or the teacher-proposing generalized DA algorithm to reach one or the other allocation.

We now state our main result. The proof is provided in Appendix D.2:

Proposition 1. *Under assumptions (A1)-(A2):*

(i) *The wage schedule and allocation resulting from the school-proposing generalized DA algorithm reaches each of the policy objectives (i) and (ii) at the lowest cost conditional on stability.*

(ii) *The allocation reached by the algorithm is implementable under the actual assignment mechanism by fixing wages to the accepted wage in each school.*

[31] This restriction implicitly requires that there are enough high quality teachers to fill at least one vacancy per school.

[32] Hence, preference over groups of teachers are responsive (Roth and Sotomayor, 1992).

Hence, we can use the school proposing generalized DA algorithm to derive the cost-efficient wage bonus policy that would achieve either policy objective (i) or (ii) under the assignment mechanism currently in place in Peru.[33]

Table 5 presents summary statistics for counterfactual compensation policies, for both matching outcomes as well as the implied cost of the wage bonuses. As a benchmark, the first two columns replicate the exercise performed in the previous subsection on the evaluation of the actual wage bonus scheme. The actual policy has been effective at increasing the share of schools with filled vacancies as well as the overall quality of the recruited teachers (Panel A). While most of the benefits accrue to schools in *Extremely Rural* locations, other rural schools also benefit on average, while urban schools do not suffer any losses in matching outcomes. This evidence is consistent with the spatially disaggregated patterns depicted in Figure 12, whereby positive net inflows from the outside option partly explain the overall reallocation effect induced by the actual system of wage bonuses.

We explore a battery of counterfactual assignments computed under the matching-with-contracts algorithm described above (*Optimal Policy* in Table 5). The third and seventh columns show that by flexibly incorporating information on teacher preferences, the counterfactual policy derived under Proposition 1 achieves the same objectives of the actual system of wage bonuses at a much lower cost—23% of the total cost for objective (i) (one-filled vacancy per school) and 12% for objective (ii) (one high-quality teacher per school). Attracting competent teachers is significantly more costly than merely filling vacancies. While the counterfactual policy shown in the fourth column would fill at least one vacancy in every school at a lower cost than the actual policy, it would take a total cost that is almost seven times the budget of the actual policy to fill every school with a teacher with the median competency level of urban areas in the status quo (eighth column). This can be explained by the fact that such objective would entail attracting approximately 4,000 high-quality applicants from the outside option. The share of unassigned high-quality teachers goes from 82% in the second column two to 59% in the eighth column.

Panel B of Table 5 further characterizes the spatial distribution of the wage bonuses. While the actual wage bonus policy is heavily skewed toward schools in the *Extremely Rural* category, the most remote localities (Distance>800 minutes), which according to Figure 11 are also the least desirable for teachers, receive only 10% of the bonuses. The counterfactual

[33] One could potentially reach the same objectives at a lower total cost by making a subset of schools deviate from the optimal stable allocation and increase wages. Such deviations may be optimal from the point of view of the overall system, illustrating a classic trade-off between stability and (aggregate) efficiency generated by the presence of externalities in two-sided matching markets. Under policy objective (ii), the allocation and wages derived are cost-efficient when considering the set of high quality teachers only. Any additional cost incurred by hiring low quality teachers is not taken into account.

Table 5: Counterfactual Policy Evaluation

Policy Objective			One Filled Vacancy per School				One High-Quality Teacher per School			
Wage Schedule	No Bonus	Actual Policy	Optimal Policy	Optimal Policy	Optimal Policy	Optimal Policy	Optimal Policy	Optimal Policy	Optimal Policy	Optimal Policy
Additional Features			Actual Allocation		Equal Amenities	Targeted Supply Increase	Actual Allocation		Equal Amenities	Targeted Supply Increase
Panel A: Matching Outcomes										
% Filled Schools	70.84	81.85	81.85	100	100	100	72.95	100	100	100
in Extremely Rural	55.43	75.99	75.99	-	-	-	59.42	-	-	-
in Rural	78.88	85.03	85.03	-	-	-	79.94	-	-	-
in Moderately Rural	84.73	88.36	88.36	-	-	-	85.11	-	-	-
in Urban	88.47	87.97	87.97	-	-	-	88.47	-	-	-
% Schools w. HQ Teacher	31.47	38.15	34.12	37.11	41.25	36.57	38.15	100	100	100
in Extremely Rural	16.39	28.36	21.06	23.90	29.40	22.14	28.36	-	-	-
in Rural	30.85	35.49	32.29	34.35	44.53	35.33	35.49	-	-	-
in Moderately Rural	40.46	44.85	41.22	43.51	48.09	43.89	44.85	-	-	-
in Urban	58.23	57.31	58.72	63.15	58.86	63.22	57.31	-	-	-
% Unassigned Teachers	90.45	88.85	88.85	87.51	87.44	87.30	90.09	84.84	84.86	84.82
% Unassig. HQ Teachers	85.28	82.28	84.32	83.24	81.80	83.46	82.28	59.37	59.50	59.37
Panel B: Wage Bonus (in millions of Soles)										
Total Cost	0	2.35M	0.55M	1.85M	1.26M	1.12M	0.29M	16.46M	13.64M	16.07M
Share of Total Cost										
in Extremely Rural	-	0.794	0.848	0.787	0.781	0.743	0.867	0.619	0.588	0.619
Dist.$\in [0, 400min]$	-	0.683	0.592	0.274	0.226	0.349	0.798	0.445	0.419	0.448
Dist.$\in [400, 800min]$	-	0.216	0.265	0.244	0.228	0.266	0.167	0.238	0.239	0.238
Dist.$> 800min$	-	0.102	0.142	0.481	0.546	0.385	0.035	0.317	0.342	0.315
in Rural	-	0.159	0.113	0.120	0.102	0.143	0.099	0.218	0.213	0.217
in Moderately Rural	-	0.039	0.022	0.031	0.023	0.040	0.026	0.058	0.063	0.058
in Urban	-	0.008	0.016	0.062	0.094	0.074	0.009	0.105	0.137	0.106

NOTES. This table displays the outcomes of different allocations that would result from counterfactual wage bonus policies under the assignment mechanism currently in place in Peru. For each counterfactual scenario, Panel A, describes the matching outcome by showing, by rurality category, the share of schools with at least one filled vacancy, the share of schools with at least one high-quality teacher, and the share of teachers in the outside option. Panel B displays the distribution of the counterfactual wage bonuses. *No Bonus* depicts the counterfactual scenario without all the bonuses currently in place. *Actual Policy* details the actual allocation and wage bonus policy. The remaining columns *Optimal Policy* describe the stable allocations and associated wage schedules resulting from the procedure described in Proposition 1 for both policy objectives.

policy, instead, targets those very remote localities more aggressively with almost half of the bonuses for achieving objective (i) and one-third of the bonuses for objective (ii). Urban localities receive almost no wage bonuses under the actual policy, but they are assigned a fair share of those (10% of the total cost) under the counterfactual policy when it comes to attracting high-quality teachers. This result may be explained by the fact that some urban localities may lack infrastructures and amenities that competent teachers value (see Table 4), which is reinforced by the upward pressure on wages due to competition among schools for relatively scarce high-quality teachers.

We next use our framework to assess the relative cost-effectiveness of additional policy instruments that may complement wage incentives in reducing spatial inequalities in the allocation of public-sector teachers. On the demand side, we remove all structural inequalities by considering a scenario where all the locality and school characteristics that potentially explain teachers' preferences are equalized across the country. Investing in local infrastructures in our setting would entail saving between 20% and 30% of the total cost in order to achieve the two policy objectives. An alternative policy consists in training prospective teachers to increase the pool of local applicants in the most disadvantaged locations. The counterfactual simulations shown in Table 5 mimic this supply-side intervention by "cloning" the four teachers who are most closely located to each of the 500 schools that propose the highest wages under the optimal policy. This gives a total of 2,000 new teachers –i.e., a 3% increase with respect to the overall number of applicants. Place-based incentives aimed at enhancing the local supply of teachers would entail saving 40% of the total cost that is needed to achieve objective (i). This result highlights the predominant roles of moving costs and of the ethnolinguistic match effects in explaining teachers' preferences over job postings in our setting (see Figure 9).[34]

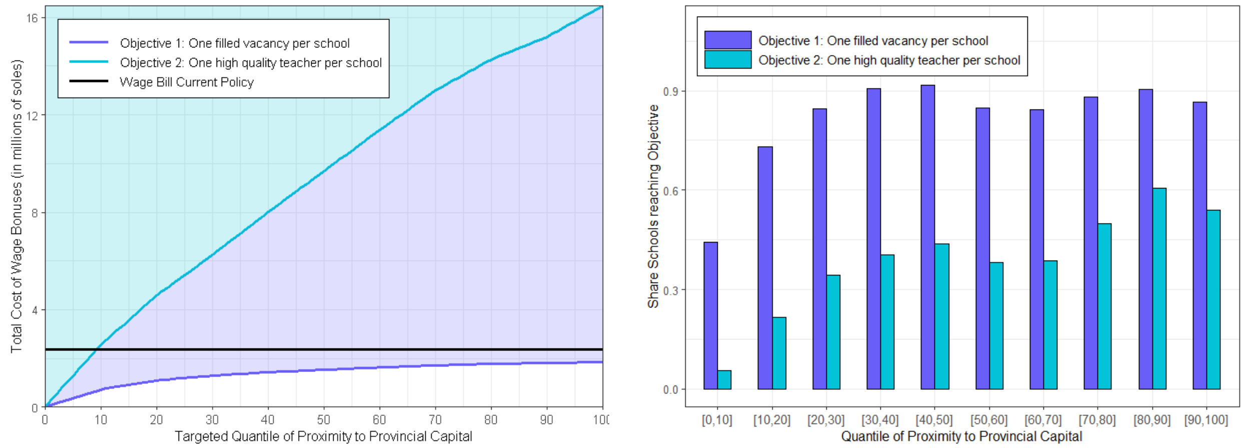
It is also possible to selectively target the counterfactual bonus policy by allowing only a pre-specified subset of schools to increase wages. For example, one could be interested in knowing what would be the cost-efficient way of filling at least one vacancy or recruiting one high-quality teacher in every school belonging to a given quantile of the distribution of the proximity to the provincial capital. Figure 14 plots the results of this exercise. The cost-effective frontiers are concave, suggesting that achieving our policy objectives is more expensive when targeting the most remote locations. This is consistent with the results reported in Panel B, which document that the actual policy is falling short on both objectives within those areas.

Panel A of Figure 14 confirms the findings reported in Panel B of Table 5, namely that attracting high-quality teachers is more challenging than filling vacancies, and hence we see that the associated cost of the policy grows large very rapidly. However, by targeting the schools in the bottom decile of the proximity distribution, the counterfactual policy dramatically improve on the actual policy for the intensive-margin objective at the same cost in terms of the wage bonuses (see the light-blue line in Panel A). Only 5% of the schools in the bottom decile of the proximity distribution have a high-quality teacher under the actual policy (see Panel B), compared to 100% of these schools in the counterfactual scenario.

There is, therefore, large scope for improvement in the actual policy by reallocating resources towards specific locations when it comes to fulfilling both policy objectives. Evidence on the concavity of the achievement production function with respect to the appointment

[34] The supply-side policy does not specifically target the overall quality of the pool of matched teachers. Hence, it is not surprising that there are no cost-advantages for achieving objective (ii) under this counterfactual.

Figure 14: Cost-Effective Frontiers



a) Optimal Policy **b) Actual Policy**

NOTES. Panel A plots the total cost of the optimal policy targeting groups of schools which location's belong to different deciles of the remoteness distribution. Panel B plots the share of filled schools with at least one filled vacancy and the share of schools with at least one high quality teacher by decile of the remoteness distribution.

of a high-quality teacher (see Figure 6) documents that students in the most remote schools are likely to be those that benefit the most from policies aimed at leveling the playing field. In these schools, a back-of-the-envelope calculation based on the RD estimates suggests that the share of students in the bottom two deciles of the test score distribution would decrease from 80% under the actual policy to less than 50% in the counterfactual policy regime at the same total cost for the government.[35]

7 Conclusion

Teachers are a central input to the education production function and better teachers have been shown to positively affect student outcomes, both in the short term and in the medium term (Chetty et al., 2014a,b). Providing qualified teachers with the right set of incentives to (re-)locate across the country may be one promising alternative to improve education opportunities in relatively disadvantaged areas.

Three distinctive features of our setting allow us to study teacher compensation policies and their potential for mitigating the deep and historical inequality in Peru; a large devel-

[35]This estimate is likely to be a lower bound since the corresponding simulated effects on teacher quality of the counterfactual policy vis-a-vis the actual policy are 2-3 times larger than the corresponding threshold-crossing effects reported in Section 4. The average of the standardized teacher competency scores for the schools in the first decile of the proximity distribution is -0.72 under the actual policy and it goes up to 0.50 in the counterfactual policy. Analogously, the average share of filled vacancies for the schools in these remote locations goes from 36.2% under the actual policy to 96.8% in the counterfactual policy.

oping country characterized by a wide array of heterogeneity in geography, language, and ethnicity. First, the government uses a centralized matching platform that acts as a market clearinghouse between prospective teachers and school vacancies. Second, we rely on high-quality administrative data that link information on (i) job openings for all public schools in the country, (ii) detailed records on job applications for the universe of public-sector teachers, and (iii) student achievement in standardized tests. Third, the introduction of a wage bonus policy for positions in hard-to-staff schools with replicable and arbitrary cutoff rules provides a credible source of variation to study the effects of teacher compensation on geographic sorting.

Our first contribution is to show causal evidence that increasing teacher pay at disadvantaged locations has important selection effects. We find that unconditional wage increases are successful in attracting more competent teachers to public schools. We also document that students in schools that offer higher wages perform significantly better in standardized achievement tests. This effect can be mostly explained by large improvements at the bottom of the distribution of student test scores, and it is entirely driven by the inflow of new teachers across schools. In fact, the policy effect on student outcomes is large and significant for schools that had openings during the period when the policy was in place, while it is estimated to be a precise zero in schools where no new openings were available, reinforcing the argument that the selection mechanism is the driver of the results.

We then turn to quantify the way teachers trade off wages with local school and community amenities by leveraging geocoded data on applications and job postings from the centralized assignment system. The model estimates shed light on the channels through which teachers sort across locations and provide key insights on alternative policy levers beyond wage incentives that may be effective in reducing inequality in access to qualified teachers. In our model, teachers have heterogeneous preferences for locality and school amenities that are unequally distributed throughout the country. While wage profiles are rigid and do not fully take take into account these trade offs, more competent teachers seem to be more sensitive to compensation.

Overall, the evidence presented here suggests that policymakers can increase equity in the market for public-sector teachers through wage policies that take into account teacher heterogenous preferences while at the same time enhancing the efficiency of the overall system. We implement this insight by recasting the current assignment algorithm in a more general matching framework in which schools can sequentially post higher wages in order to achieve a more equal access to (high-quality) teachers across the country. The resulting alternative wage schedules are more cost-effective than the actual policy implemented in Perú and can help reduce structural inequality in access to learning opportunities. In comparison, a rigid system that ignores teacher preferences will indirectly reinforce such inequalities.

Many organizations routinely employ algorithmic pricing strategies that effectively account for demand and supply considerations in real time. Our study illustrates the untapped potential of leveraging this approach in the context of the public sector. By incentivizing sorting toward jobs or locations where working conditions are less appealing compensation policies can feasibly alter the spatial distribution of public-sector employees. These considerations can be relevant in a variety of other settings that typically feature rigid wage profiles, whereby such reallocation process is likely consequential for the quality, equity, and efficiency of public good provision.

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Appendices

A Descriptive Evidence

Table A.1: Applicant Characteristics

	Only contract		Contract and permanent		Only Permanent	
	Mean	Sd	Mean	Sd	Mean	Sd
Age	37.72	6.934	34.50	5.802	34.48	5.465
Female	0.698	0.459	0.837	0.369	0.696	0.460
Indigenous	0.300	0.458	0.119	0.324	0.189	0.391
University degree	0.289	0.453	0.454	0.498	0.415	0.493
Curricular knowledge	40.29	13.17	67.95	6.578	70.04	7.408
Competency score	89.81	24.65	145.2	11.11	148.1	12.45
New entrant	0.344	0.475	0.313	0.464	0.166	0.372
Prior teaching experience in public schools	0.776	0.417	0.737	0.440	0.868	0.339
Prior teaching experience in private schools	0.448	0.497	0.739	0.439	0.619	0.486
Previous school: Urban	0.321	0.467	0.673	0.469	0.499	0.500
Previous school: Extremely rural	0.291	0.454	0.0852	0.279	0.189	0.391
Previous school: Rural	0.255	0.436	0.133	0.340	0.188	0.391
Previous school: Moderately rural	0.132	0.339	0.108	0.311	0.124	0.330
Number of teachers	119490		7630		8916	

NOTES. This table reports the summary statistics for the applicants to the 2015 and 2017 centralized teacher assignment system. Applicants are split in three groups: i) applicants to the contract teaching positions only; ii) unassigned applicants to the permanent teaching positions who applied to a contract teaching position; iii) applicants to the permanent teaching positions (assigned). The information on whether the applicant speaks a Peruvian indigenous language (*Indigenous*) is available for the first round of the assignment system only (2015). *Newentrant* is a dummy variable that takes value 1 if the teacher has not been employed as public sector teacher (i.e. she was not observed in *NEXUS* teacher occupation and payroll system) before the teacher assignment process. The (self-reported) information on applicants' prior teaching experience in public and private schools is collected at the time of the application.

Table A.2: School and Locality Characteristics

	Rural schools		Urban Schools	
	Mean	Std. Dev.	Mean	Std. Dev.
Panel A: School characteristics				
Number of students	40.16	(45.89)	339.9	(262.0)
Bilingual school	0.249	(0.432)	0.00864	(0.0926)
Single-teacher school	0.393	(0.488)	0.0151	(0.122)
Multigrade school	0.466	(0.499)	0.0868	(0.282)
Number of teachers	5.092	(4.050)	24.59	(13.58)
% of permanent teachers	0.677	(0.468)	0.807	(0.394)
% of certified contract teachers	0.164	(0.371)	0.114	(0.317)
% of non-certified contract or other teachers	0.158	(0.365)	0.0790	(0.270)
% of competent teachers	0.210	(0.407)	0.386	(0.487)
Panel B: Student characteristics				
Math test scores (std)	-0.438	(1.005)	0.125	(0.962)
Math test scores: % Below basic	0.233	(0.423)	0.0681	(0.252)
Math test scores: % Proficient	0.147	(0.354)	0.285	(0.452)
Spanish test scores (std)	-0.568	(0.924)	0.162	(0.961)
Spanish test scores: % Below basic	0.223	(0.416)	0.0513	(0.221)
Spanish test scores: % Proficient	0.141	(0.348)	0.368	(0.482)
Panel C: School infrastructure				
No water	0.311	(0.463)	0.0355	(0.185)
No electricity	0.233	(0.423)	0.0127	(0.112)
Cafeteria	0.284	(0.451)	0.211	(0.408)
Computer	0.619	(0.486)	0.932	(0.252)
Kitchen	0.392	(0.488)	0.372	(0.483)
Internet	0.186	(0.389)	0.912	(0.283)
Library	0.207	(0.405)	0.564	(0.496)
Sport facility	0.190	(0.392)	0.614	(0.487)
Gym	0.0126	(0.111)	0.118	(0.323)
Stadium	0.00268	(0.0517)	0.0419	(0.200)
Panel D: Locality infrastructure				
Electricity	0.803	(0.398)	0.997	(0.0553)
Sewage	0.259	(0.438)	0.915	(0.279)
Library	0.0166	(0.128)	0.430	(0.495)
Doctor	0.324	(0.468)	0.869	(0.338)
Internet access point	0.0554	(0.229)	0.845	(0.362)
Village phone	0.0498	(0.218)	0.0928	(0.290)
Drinking water	0.582	(0.493)	0.945	(0.228)

Notes. This table reports the summary statistics for the universe of rural and urban primary schools in Peru over the period 2016-2018. The first panel describes the baseline characteristics of each type of school (size, bilingual spanish/indigenous language curriculum) for the year 2016, and the teaching staff composition (pooling together the post-recruitment drives years 2016 and 2018). The second panel summarizes students' achievement in the 2016 and 2018 standardized test. The third and the fourth panel describes the quality and quantity of school infrastructures and locality amenities, as measured by the 2016 school census.

Table A.3: Applicant Survey (Participation and Choice Attributes)

	All Teachers Rank				Score in Top Quartile Rank			
	1^{st}	2^{nd}	3^{rd}	In Top 3	1^{st}	2^{nd}	3^{rd}	In Top 3
Panel A: Why did you apply to the centralized assignment mechanism? (% of respondents)								
Career	33.77	30.35	20.57	84.69	33.73	29.97	21.35	85.05
Stability	51.08	17.04	14.76	82.88	50.66	18.26	13.92	82.84
Formation Opportunities	9.63	29.15	21.81	60.59	9.57	26.73	20.32	56.62
Better Wage Opportunities	2.08	9.51	23.84	35.43	2.14	11.41	22.75	36.30
Social Benefits	1.04	7.78	7.96	16.78	1.10	7.00	7.58	15.68
Prestige	1.71	4.28	7.19	13.18	1.62	3.24	7.73	12.59
18 mil Soles Incentive	0.69	1.89	3.87	6.45	1.18	3.39	6.33	10.90
Panel B: What are the most important characteristic for your ranked choices? (% of respondents)								
Close to House	44.17	11.66	8.00	63.83	49.77	13.22	8.76	71.75
Safe	10.66	24.19	19.25	54.10	7.65	24.50	19.35	51.50
Well Connected	9.69	20.62	20.20	50.51	8.23	18.70	19.67	46.60
Prestige	17.92	14.12	12.29	44.33	21.13	15.77	12.68	49.58
Cultural Reasons	10.61	9.67	12.31	32.59	7.58	9.45	12.61	29.64
Good Infrastructure	2.02	8.40	12.86	23.28	1.81	7.23	11.83	20.87
Good Students	1.24	4.52	6.08	11.84	0.84	4.36	5.95	11.15
Possibility other Jobs	1.93	3.72	4.90	10.55	1.62	4.10	4.71	10.43
Career	1.76	3.10	4.09	8.95	1.36	2.67	4.44	8.47

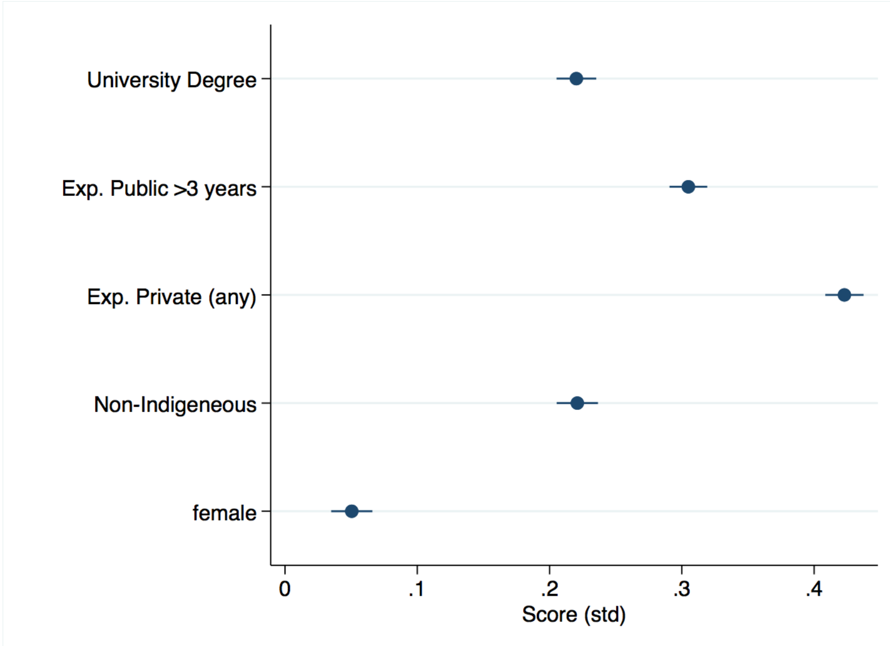
Notes. This table displays the share of the 5,553 survey respondents that chose the corresponding answers to Question A and B. The first three columns show which answer they chose and how they ranked them (by order of importance) while column 4 shows the share of respondents that listed the corresponding choice in their top 3 reasons. The last four columns display the same results for respondents that scored above the top quartile of the test score distribution for tenured teachers.

Table A.4: Applicant Survey (Strategy and Information)

	All	Score in Top Quartile
Panel A: Strategic behavior (% of respondents)		
Preferred school in concurso	63.36	61.37
If preferred school in concurso, which rank?		
Ranked 1^{st}	84.26	88.93
Ranked 2^{nd}	6.28	3.51
Ranked 3^{rd}	2.31	1.32
Ranked 4^{th}	0.71	0.66
Ranked 5^{th}	0.95	0.66
Not Ranked	5.48	4.93
If not ranked first, why?		
High demand and score too low	64.91	41.82
Remuneration not attractive	3.51	5.45
Other	31.58	52.73
Panel B: Information about first choice (% of respondents)		
Had prior information about first choice	50.97	54.01
Does your first choice benefit from wage bonus?		
Yes	16.42	15.08
No	54.53	62.69
Do not know	29.04	22.23
Expected wage - actual wage (in %)	-11.02	-8.97

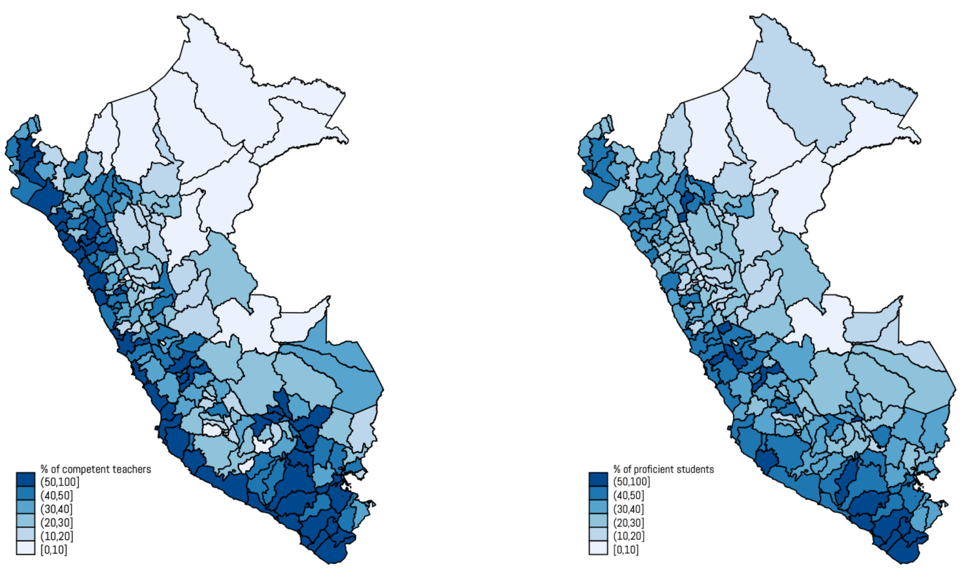
Notes. This table displays the answers of the 5,553 survey respondents to the corresponding questions. The last columns displays the same results for respondents that scored above the top quartile of the test score distribution for tenured teachers.

Figure A.1: Teacher Characteristics and Standardized Competency Scores



Notes: This figure shows OLS estimates and the associated 95 percent confidence intervals of the effect of individual teacher characteristics on the standardized competency score undertaken by all the applicants for a primary school vacancy in the context of the national recruitment drive in 2015 (see Section 3.2).

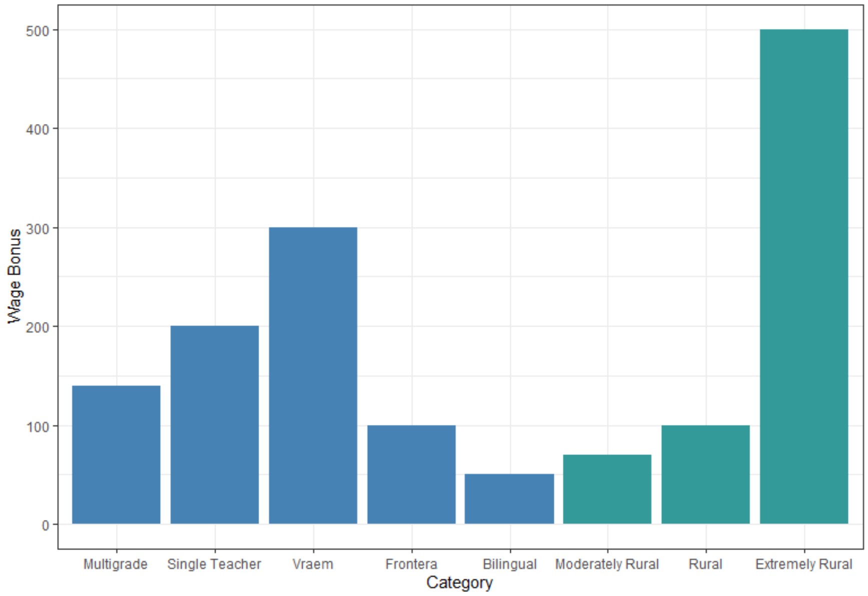
Figure A.2: Geographic Distribution of Teacher Competency and Student Achievement



a) % Competent Teachers **b) % of Proficient Students**

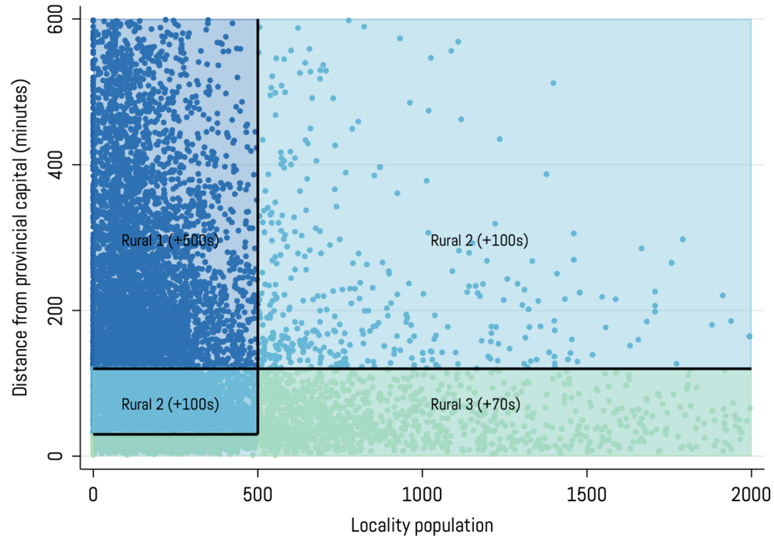
Notes: This figure depicts the geographical variation in the share of competent teachers (panel A) and the share of proficient students (panel B) within each province of Peru. Proficient students are defined as those who attain a proficient (*Satisfactorio*) achievement level in Math and/or Spanish. Similarly, competent teachers are defined as those who attain at least 60% of correct answers in the curricular and pedagogical knowledge module of the standardized test. The reported shares are obtained by pooling the data across two school years (2016 and 2018).

Figure A.3: The Different Wage Bonuses for Disadvantaged Schools

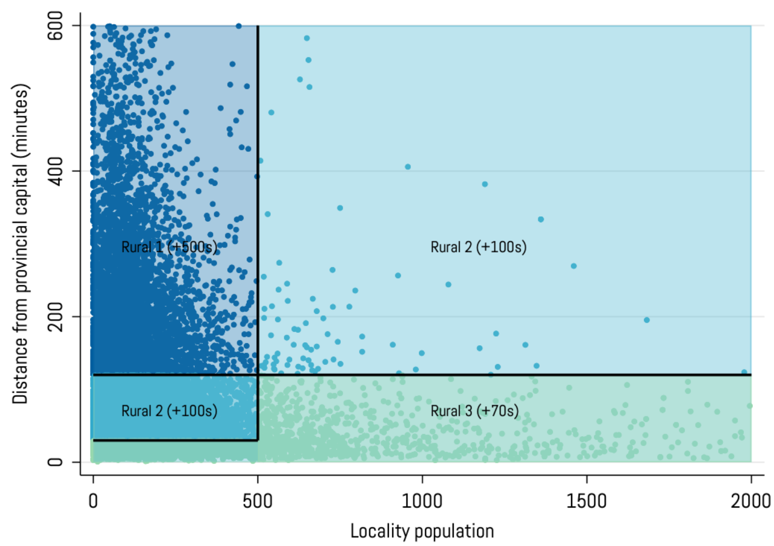


Notes. This figure shows the monetary amount in Peruvian Soles for the different wage bonuses implemented by the Government as of December 2015. Vraem correspond to schools located in the Valle de los Rios Apurimac, Ene y Mantaro which is extremely poor and under the control of drug cartels. Frontera categorizes schools that are close to the frontier of the country.

Figure A.4: The Distribution of Rural Schools over Population and Remoteness



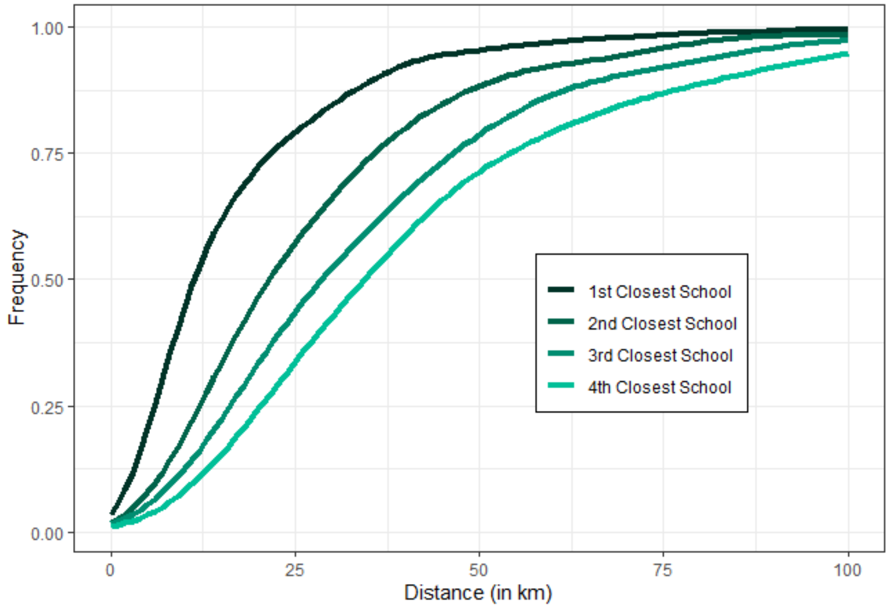
a) Schools with Vacancies in 2015-2017



b) Schools without Vacancies in 2015-2017

Notes: This figure shows the spatial distribution of rural primary schools along the two dimensions that determine the assignment of the wage bonus. *Extremely Rural* schools are the purple dots, *Rural* are light blue and *Moderately Rural* schools are green.

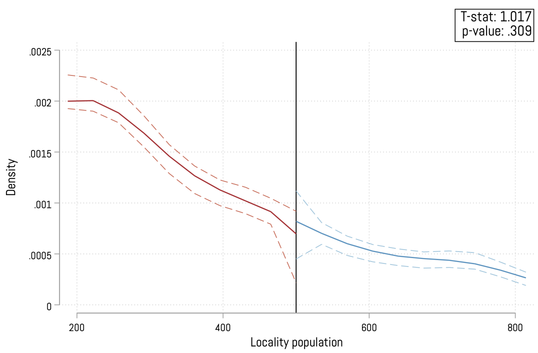
Figure A.5: Distance from Schools Just Above the Population Cutoff



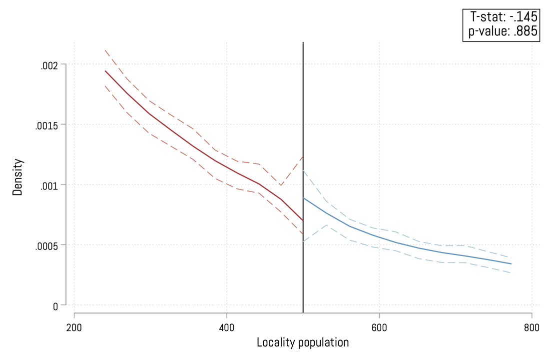
NOTES: This figure plots the CDF of the distance in Kilometers for the four closest below-cutoff schools from schools just above the cutoff. The sample includes schools with an open position for contract teachers during the 2015 and 2017 recruitment drives.

B RD Evidence

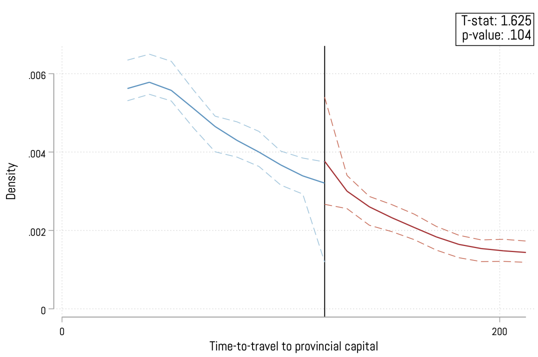
Figure B.1: Manipulation charts



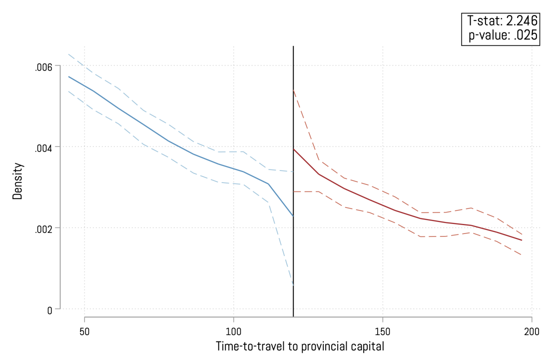
a. Population (2015)



b. Population (2017)



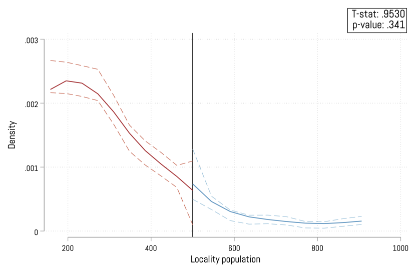
c. Time-to-travel (2015)



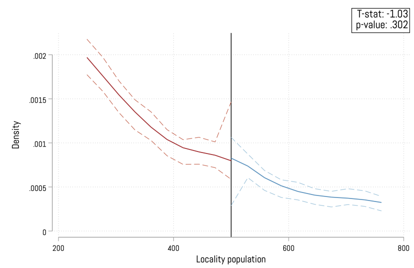
d. Time-to-travel (2017)

Notes. The figure displays the empirical densities with the corresponding confidence intervals for two running variables (population and time-to-travel) for each of the years in which the teacher recruitment drive was conducted (2015 and 2017). The density is computed using the local-polynomial estimator proposed in Cattaneo et al. (2020), and the figures show the 95% confidence intervals. The sample includes all schools with a permanent or contract teacher opening in the corresponding year.

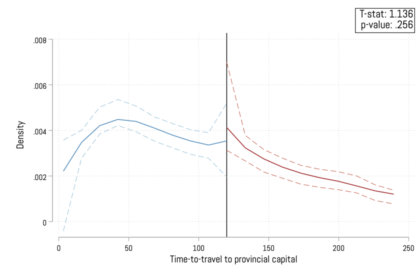
Figure B.2: Manipulation Charts - Schools with a Vacancy for Permanent Teachers



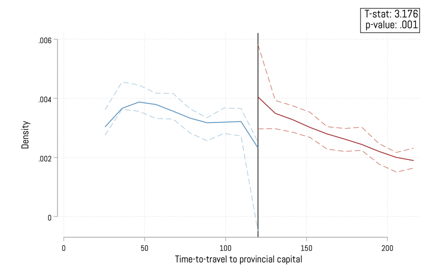
a. Population (2015)



b. Population (2017)



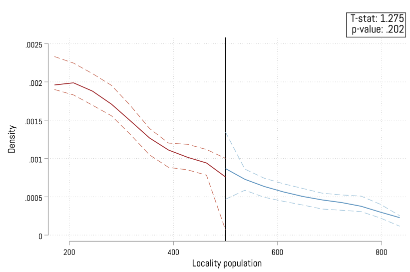
a. Time-to-travel (2015)



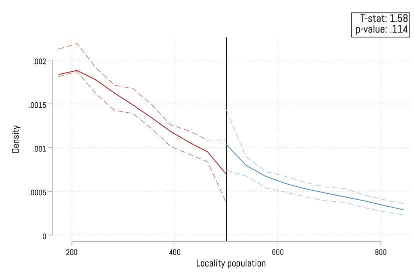
b. Time-to-travel (2017)

NOTES. The figure displays the empirical densities with the corresponding confidence intervals for two running variables (population and time-to-travel) for each of the years in which the teacher recruitment drive was conducted (2015 and 2017). The density is computed using the local-polynomial estimator proposed in Cattaneo et al. (2020), and the figures show the 95% confidence intervals. The sample includes only schools with a permanent teacher opening in the corresponding year.

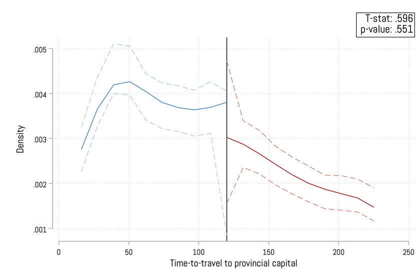
Figure B.3: Manipulation Charts - Schools with a Vacancy for Contract Teachers



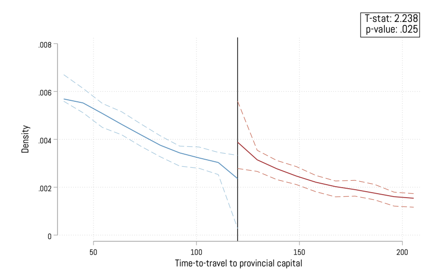
a. Population (2015)



b. Population (2017)



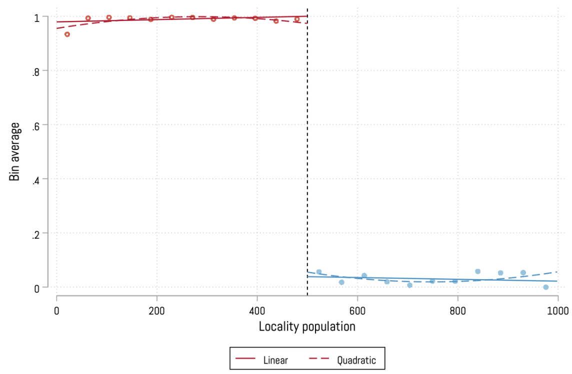
a. Time-to-travel (2015)



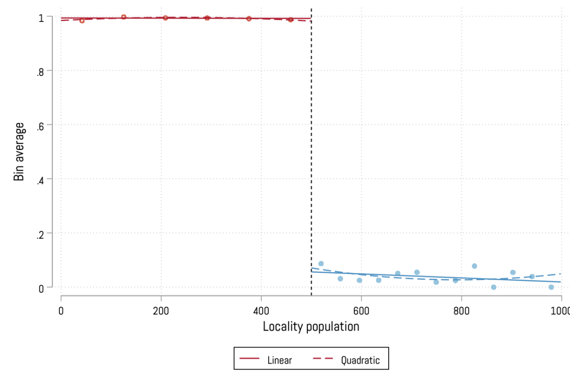
b. Time-to-travel (2017)

NOTES. The figure displays the empirical densities with the corresponding confidence intervals for two running variables (population and time-to-travel) for each of the years in which the teacher recruitment drive was conducted (2015 and 2017). The density is computed using the local-polynomial estimator proposed in Cattaneo et al. (2020), and the figures show the 95% confidence intervals. The sample includes only schools with a contract teacher opening in the corresponding year.

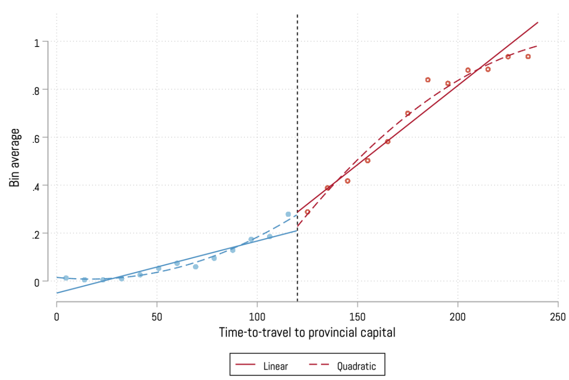
Figure B.4: First Stage for Different Years and Treatment Status



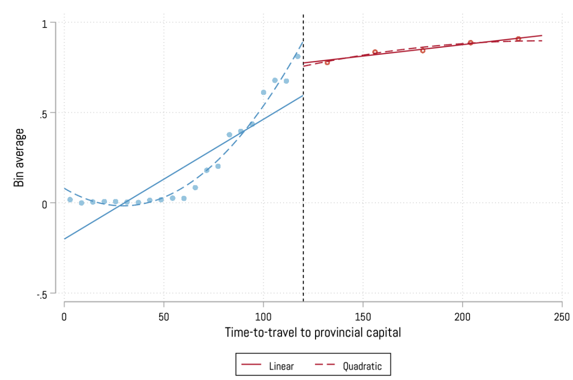
a. Treatment 2017; RV: population 2015



b. Treatment 2015; RV: population 2017



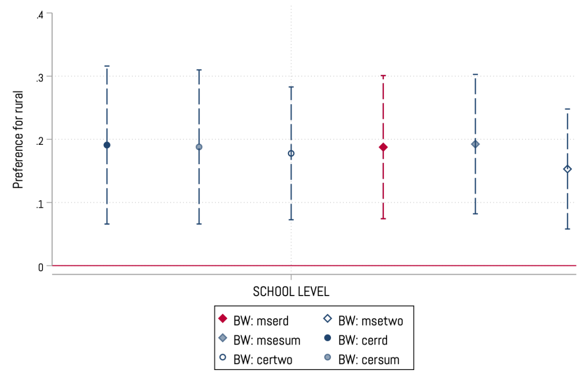
c. Treatment 2015; RV: time-to-travel 2017



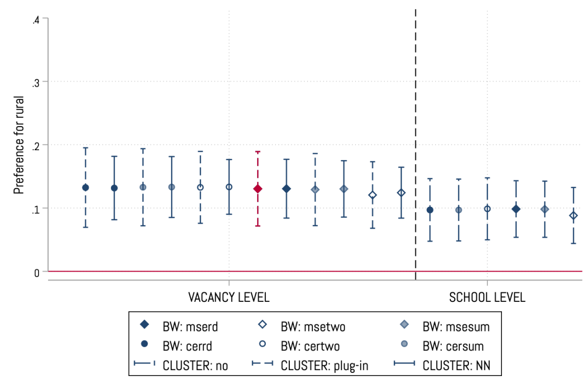
d. Treatment 2017; RV: time-to-travel 2015

Notes. The figures show the probability that a school is classified as *Extremely Rural* in each year (2015 and 2017) plotted against the two different running variables (Population and time-to-travel) for the opposite year (2017 and 2015, respectively). The regression lines are computed using linear and quadratic polynomials.

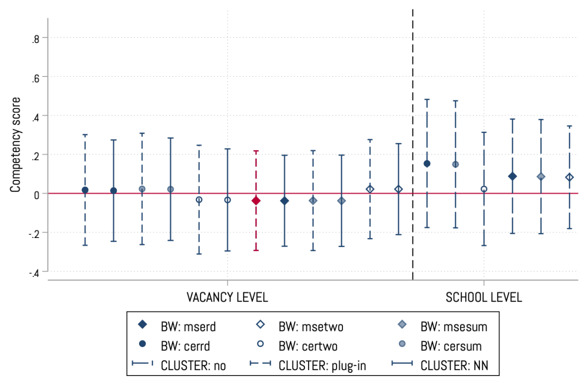
Figure B.5: Robustness to Alternative RD Specifications – Teacher Outcomes



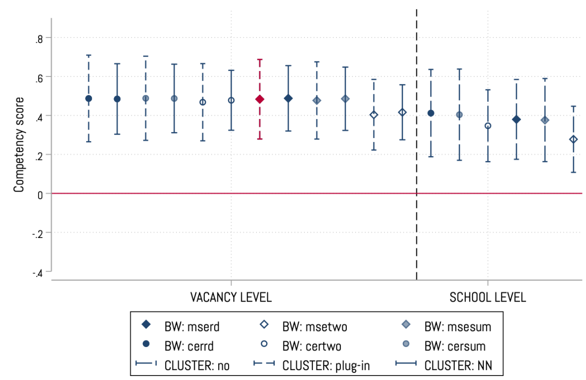
a. Stated Preferences, Permanent teachers



b. Revealed Preferences, Contract teachers



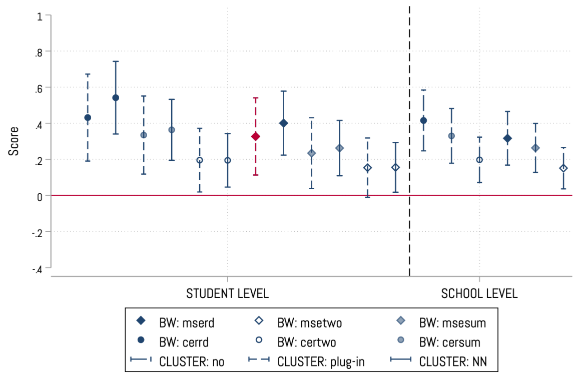
c. Competency score, Permanent teachers



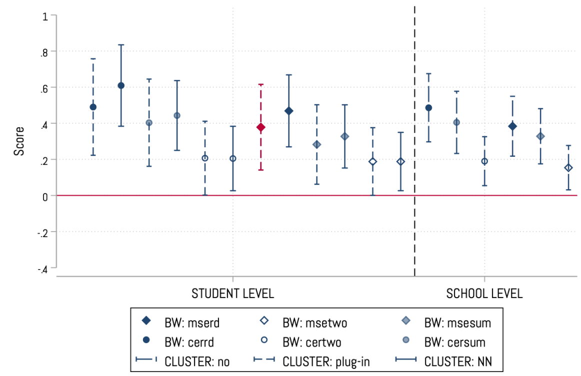
d. Competency score, Contract teachers

Notes. The figure shows how the applicants' preferences and quality vary based on the distance from the population threshold. Panels A and C focus on the assignment process of permanent teachers. In Panel A the outcome variable is a dummy equal to one if a school was mentioned in at least one application, while in Panel C the outcome variable is the standardized (total) score obtained in the centralized test by the newly-assigned permanent teacher. Panels B and D are analogous to A and C for the assignment process of contract teachers. Panel B uses as outcome variable the rank in which a vacancy was chosen in the serial dictatorship mechanism (normalized so that it takes value from zero to one), while Panel D uses the standardized score obtained in the centralized test by the newly-assigned contract teacher. Markers indicate the robust bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within different specifications for the optimal bandwidths. These are: *i.* one common mean-square error (MSE) optimal bandwidth (BW: mserd); *ii.* two different MSE-optimal bandwidths, above and below the cutoff (BW: msetwo); *iii.* one common MSE-optimal bandwidth for the sum of regression estimates (BW: msesum); *iv.* one common coverage error rate (CER) optimal bandwidth (BW: cerrd); *v.* two different CER-optimal bandwidths, above and below the cutoff (BW: certwo); *vi.* one common CER-optimal bandwidth for the sum of regression estimates (BW: cersum). Vertical lines indicate confidence intervals (at the 95% level) obtained from different estimation procedures: heteroskedasticity-robust plug-in residuals (CLUSTER: no); cluster-robust plug-in residuals (CLUSTER: plug-in); cluster-robust nearest neighbor (CLUSTER: NN). The vertical dotted line separates estimates based on whether they are obtained from regressions where the unit of observation is the student (on the left) or the school (on the right). In the latter case, the outcome variables are school-level averages

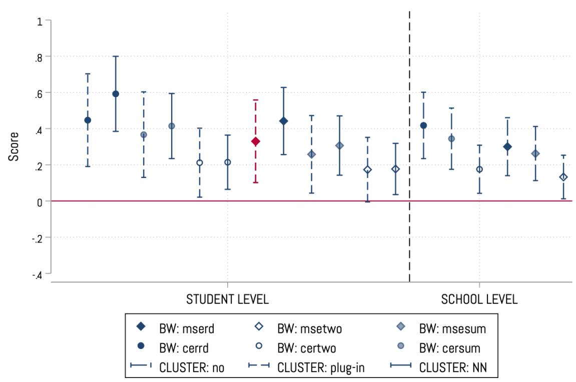
Figure B.6: Robustness to Alternative RD Specifications – Student Outcomes



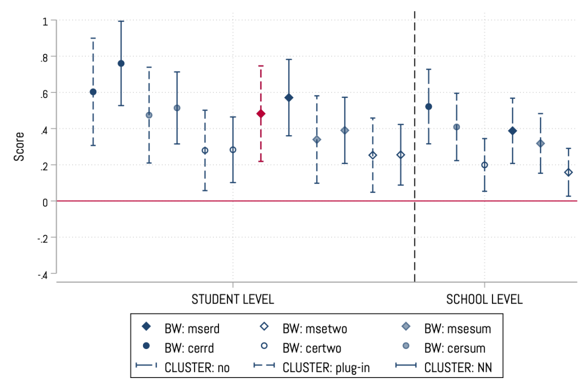
a. Spanish scores, Any vacancy



b. Math scores, Any vacancy



c. Spanish scores, Short-Term vacancy



d. Math scores, Short-Term vacancy

Notes. This figures shows the effect of crossing the population threshold on student achievement under different specifications. The outcome variable is the average of the standardized 2018 test scores in Math and Spanish for students in the fourth grade. The sample includes schools that had an open vacancy for contract teachers the 2015 or 2017 centralized recruitment drive. Markers indicate the robust bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within different specifications for the optimal bandwidths. These are: *i.* one common mean-square error (MSE) optimal bandwidth (BW: mserd); *ii.* two different MSE-optimal bandwidths, above and below the cutoff (BW: msetwo); *iii.* one common MSE-optimal bandwidth for the sum of regression estimates (BW: msesum); *iv.* one common coverage error rate (CER) optimal bandwidth (BW: cerrd); *v.* two different CER-optimal bandwidths, above and below the cutoff (BW: certwo); *vi.* one common CER-optimal bandwidth for the sum of regression estimates (BW: cersum). Vertical lines indicate confidence intervals (at the 95% level) obtained from different estimation procedures: heteroskedasticity-robust plug-in residuals (CLUSTER: no); cluster-robust plug-in residuals (CLUSTER: plug-in); cluster-robust nearest neighbor (CLUSTER: NN). The vertical dotted line separates estimates based on whether they are obtained from regressions where the unit of observation is the student (on the left) or the school (on the right). In the latter case, the outcome variables are school-level averages

Table B.1: Wage increases around the population cutoff

Panel A: Permanent teacher			
	(1)	(2)	(3)
	Low bonus	High bonus	Average
High Bonus	23.321	369.796	224.931
	(17.861)	(27.099)	(29.931)
Mean dep. var. (Low Bonus)	2012.572	2107.689	2061.620
Bandwidth	149.828	307.458	222.189
Schools	361	1146	1181
Observations	599	2340	2365
Panel B: Contract teacher			
	(1)	(2)	(3)
	Low bonus	High bonus	Average
High Bonus	45.537	386.965	255.993
	(11.026)	(33.834)	(34.418)
Mean dep. var. (Low Bonus)	1906.026	1956.918	1928.570
Bandwidth	144.376	183.205	178.720
Schools	467	537	1042
Observations	827	1462	2434

Notes. This table reports the effect of crossing the population threshold on the wages of permanent (Panel A) and contract teachers (Panel B). In all columns, the outcome variable is the gross salary, which includes both the baseline wage and the bonuses. In Column (1), the sample includes only schools in rural locations whose travel time to the provincial capital is between 30 and 120 minutes, so that crossing the 500 inhabitant cutoff from above implies moving from a Moderately Rural to a Rural area. Similarly, in Column (2) the sample includes only schools in rural locations whose travel time to the provincial capital is above 120 minutes, so that crossing the 500 inhabitant cutoff from above implies moving from a Rural to an Extremely Rural area. In Column (3), the sample is the union of that in Column (1) and (2): it includes all schools in rural locations whose travel time to the provincial capital is above 30 minutes. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.2: Covariate Smoothness around the Population Cutoff

	2015			2017		
	(1) Any vac.	(2) Permanent	(3) Contract	(4) Any vac.	(5) Permanent	(6) Contract
School characteristics						
Number of students	-2.912	5.555	-18.543	-1.045	-4.498	-3.479
	(10.290)	(11.990)	(11.635)	(6.499)	(8.513)	(6.736)
Indigenous language students	-0.038	-0.052	-0.056	0.017	-0.042	0.014
	(0.097)	(0.143)	(0.108)	(0.067)	(0.087)	(0.075)
% indigenous language students	-0.022	0.028	-0.030	-0.008	-0.040	0.015
	(0.085)	(0.112)	(0.103)	(0.046)	(0.066)	(0.065)
% proficient students (math)	3.863	-0.939	4.796	1.331	-4.160	2.993
	(3.144)	(7.601)	(3.305)	(3.477)	(3.511)	(3.722)
% proficient students (spanish)	6.294	5.182	8.202**	-2.264	-5.437	0.278
	(4.070)	(5.609)	(4.114)	(3.775)	(4.073)	(4.049)
Village amenities						
Electricity	0.062	0.011	0.012	0.026	-0.043	0.058
	(0.090)	(0.126)	(0.083)	(0.053)	(0.064)	(0.068)
Drinking water	0.260**	0.231	0.309**	0.110	0.174	0.144
	(0.132)	(0.173)	(0.150)	(0.083)	(0.115)	(0.101)
Sewage	0.179	0.067	0.171	-0.022	-0.030	-0.001
	(0.115)	(0.153)	(0.127)	(0.070)	(0.097)	(0.080)
Medical clinic	0.056	0.030	0.066	0.000	-0.069	0.001
	(0.107)	(0.151)	(0.122)	(0.082)	(0.100)	(0.091)
Meal center	0.186**	0.246**	0.146	0.069	0.113	0.075
	(0.087)	(0.117)	(0.101)	(0.081)	(0.093)	(0.085)
Community phone	-0.007	-0.059	-0.036	-0.034	-0.033	-0.086
	(0.093)	(0.135)	(0.114)	(0.069)	(0.091)	(0.075)
Internet access point	0.054	0.153*	0.070	0.022	-0.004	0.024
	(0.058)	(0.084)	(0.079)	(0.051)	(0.059)	(0.062)
Bank	0.023*	0.000	0.031*	0.010	0.005	0.013
	(0.013)	(0.000)	(0.016)	(0.007)	(0.008)	(0.009)
Public library	0.018	-0.059	0.019	-0.004	0.002	0.006
	(0.032)	(0.049)	(0.043)	(0.023)	(0.030)	(0.016)
Police	-0.079	-0.161	-0.094	-0.056	-0.124	-0.078
	(0.082)	(0.118)	(0.097)	(0.063)	(0.089)	(0.067)
School amenities						
Distance from district municipality (min.)	-27.579	99.432	-17.468	78.389	83.076	101.385
	(112.029)	(171.377)	(128.940)	(138.805)	(173.709)	(169.936)
Teachers room	-0.033	0.016	-0.095	-0.074	-0.177**	-0.069
	(0.072)	(0.095)	(0.084)	(0.066)	(0.075)	(0.072)
Sport pitch	-0.033	0.023	-0.041	0.002	-0.033	0.020
	(0.087)	(0.098)	(0.090)	(0.059)	(0.067)	(0.069)
Courtyard	-0.061	-0.010	-0.096	-0.116	-0.074	-0.104
	(0.092)	(0.107)	(0.100)	(0.080)	(0.087)	(0.081)
Administrative office	-0.010	-0.130	-0.094	0.056	0.032	0.048
	(0.101)	(0.155)	(0.128)	(0.077)	(0.102)	(0.094)
Courtyard	0.002	0.001	0.001	-0.009	-0.025	0.002
	(0.004)	(0.001)	(0.005)	(0.014)	(0.023)	(0.004)
Computer lab	-0.004	-0.023	-0.048	0.050	0.006	0.070
	(0.087)	(0.122)	(0.113)	(0.074)	(0.099)	(0.083)
Workshop	-0.002	-0.006	-0.020	0.010	-0.013	0.002
	(0.036)	(0.066)	(0.037)	(0.029)	(0.033)	(0.033)
Science lab	0.030	0.043	0.029	0.040	0.006	0.049
	(0.062)	(0.090)	(0.076)	(0.042)	(0.043)	(0.050)
Library	0.044	-0.115	0.007	0.094	0.076	0.044
	(0.104)	(0.159)	(0.134)	(0.071)	(0.102)	(0.095)
At least a personal computer	0.030	0.045	0.043	0.075	0.125	0.103
	(0.082)	(0.118)	(0.094)	(0.073)	(0.091)	(0.074)
Electricity	0.173	0.145	0.179	0.106	0.072	0.124
	(0.114)	(0.147)	(0.132)	(0.075)	(0.093)	(0.083)
Water supply	0.276**	0.239	0.346**	0.079	0.050	0.132
	(0.128)	(0.168)	(0.144)	(0.077)	(0.084)	(0.095)
Sewage	0.183*	0.089	0.214	-0.007	0.029	0.058
	(0.102)	(0.120)	(0.131)	(0.070)	(0.107)	(0.081)

Notes. This table studies whether schools in localities just above or below the population threshold differ in terms of village and school amenities (as of 2013). Columns (1) to (3) focus on the 2015 assignment process, with schools split based on whether they had at least a permanent (column 2) or contract (column 3) vacancy (the sample in column 1 is the union of column 2 and 3). Columns (4) to (6) are the analogous of columns (1)-(2) but focus on the 2017 assignment process. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth. Robust SE in parentheses.*** p< 0.01, ** p<0.05, and *p<0.10.

Table B.3: Probability of Openings around the Population Cutoff

	All		Permanent teacher		Contract teacher	
	(1)	(2)	(3)	(4)	(5)	(6)
	Vacancy	N. of vacancies	Vacancy	N. of vacancies	Vacancy	N. of vacancies
High Bonus	-0.012	-0.119	0.004	-0.046	-0.011	-0.116
	(0.041)	(0.138)	(0.041)	(0.091)	(0.043)	(0.134)
Mean dep. var. (Low Bonus)	0.480	0.954	0.253	0.461	0.399	0.764
Bandwidth	237.233	184.699	165.436	173.385	228.761	183.478
Observations	5912	4221	3763	3929	5612	4195

Notes. This table reports the effect of crossing the population threshold on the probability that vacancy is posted (and their number) in the 2015 or 2017 assignment process. In column (1) the outcome variable is a dummy equal to 1 if the school had at least a vacancy (of any type), while in column (2) is the number of open vacancies. Columns (3)-(4) and (5)-(6) are the analogous of columns (1)-(2) but focus only on permanent and contract teachers vacancies, respectively. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.4: Monetary Incentives and Teacher Selection (2015)

Panel A: Permanent teacher			
	(1)	(2)	(3)
	Stated Preferences	Vacancy filled	Competency score
High Bonus	0.095	-0.108	0.372
	(0.085)	(0.148)	(0.384)
Bounds			[.246; .246]
Mean dep. var. (Low Bonus)	0.793	0.526	0.245
Bandwidth	238.248	209.055	152.735
Schools	552	445	170
Observations	552	604	215
Panel B: Contract teacher			
	(1)	(2)	(3)
	Revealed Preferences	Vacancy filled	Competency score
High Bonus	0.153	0.101	0.664
	(0.062)	(0.073)	(0.199)
Bounds	[.118; .181]		[.466; .74]
Mean dep. var. (Low Bonus)	0.616	0.869	-0.113
Bandwidth	156.897	200.982	144.348
Schools	402	587	365
Observations	667	978	614

Notes. This table reports the effect of crossing the population threshold on different outcomes. Panel A uses the sample of permanent teachers. In Column (1) the outcome variable is a dummy equal to one if a school was mentioned in at least one application, while in Column (2) is an indicator for whether the vacancy was filled by a certified teacher in the assignment process for permanent teachers. The regression displayed in the last column uses as outcome variable the standardized total score obtained by the teachers in the centralized test. In Columns (3) the sample is restricted to vacancies that were actually filled by a certified teacher. Panel B focuses on the selection process of contract teachers. Column (1) shows the effects on the rank in which a vacancy was chosen in the deferred acceptance mechanism (normalized so that it takes value from zero to one), while Columns (2) to (3) are analogous to those from Panel A. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014) and their bounds estimated using the procedure developed in Gerard et al. (2020). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the interval $(-BW, 0]$ (left-hand-side of the cutoff). Standard errors are clustered at the school$\times$year level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.5: Monetary Incentives and Teacher Selection (2017)

Panel A: Permanent teacher			
	(1)	(2)	(3)
	Stated Preferences	Vacancy filled	Competency score
High Bonus	0.258	0.084	-0.044
	(0.090)	(0.083)	(0.218)
Bounds			[-.517; .408]
Mean dep. var. (Low Bonus)	0.735	0.329	-0.169
Bandwidth	151.059	166.276	160.587
Schools	603	669	328
Observations	603	1240	446
Panel B: Contract teacher			
	(1)	(2)	(3)
	Revealed Preferences	Vacancy filled	Competency score
High Bonus	0.119	0.020	0.380
	(0.042)	(0.059)	(0.151)
Bounds	[.111; .119]		[.359; .362]
Mean dep. var. (Low Bonus)	0.642	0.912	0.169
Bandwidth	165.307	158.194	178.439
Schools	815	805	866
Observations	1401	1438	1482

Notes. This table reports the effect of crossing the population threshold on different outcomes. Panel A uses the sample of permanent teachers. In Column (1) the outcome variable is a dummy equal to one if a school was mentioned in at least one application, while in Column (2) is an indicator for whether the vacancy was filled by a certified teacher in the assignment process for permanent teachers. The regression displayed in the last column uses as outcome variable the standardized total score obtained by the teachers in the centralized test. In Columns (3) the sample is restricted to vacancies that were actually filled by a certified teacher. Panel B focuses on the selection process of contract teachers. Column (1) shows the effects on the rank in which a vacancy was chosen in the deferred acceptance mechanism (normalized so that it takes value from zero to one), while Columns (2) to (3) are analogous to those from Panel A. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014) and their bounds estimated using the procedure developed in Gerard et al. (2020). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the interval $(-BW, 0]$ (left-hand-side of the cutoff). Standard errors are clustered at the school×year level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.6: Monetary Incentives and Teaching Staff Composition

	Permanent Vacancy			Short-term Vacancy		
	(1)	(2)	(3)	(4)	(5)	(6)
	N. of teachers	Student/Teacher	% of permanent t.	N. of teachers	Student/Teacher	% of contract t.
High Bonus	0.124	-0.095	0.083	-0.537	0.052	-0.045
	(0.345)	(0.182)	(0.043)	(0.372)	(0.184)	(0.036)
Mean dep. var. (Low Bonus)	6.572	2.668	0.543	6.562	2.598	0.411
Bandwidth	172.891	144.740	238.703	147.124	164.956	193.869
Observations	1033	835	1599	1152	1282	1568

Notes. This table reports the effect of crossing the population threshold on the number and the composition of teaching staff in schools that had an open vacancy in the 2015 or 2017 assignment process. The sample in columns (1) to (3) includes schools that had vacancies for permanent teachers. In column (1) the outcome variable is the total number of teachers, in column (2) is the students to teachers ratio, while in column (3) is the share of permanent teachers. Columns (4) to (6) are the analogous of columns (1)-(3) for schools that had vacancies for contract teachers. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.7: Monetary Incentives and Teachers' Retention

	Permanent teachers		Contract teachers	
	(1)	(2)	(3)	(4)
	Within-year	Between-years	Within-year	Between-years
High Bonus	0.014	0.012	0.003	-0.005
	(0.020)	(0.026)	(0.007)	(0.013)
Mean dep. var. (Low Bonus)	0.905	0.099	0.970	0.919
Bandwidth	200.427	150.910	174.360	142.533
Schools	1366	998	2021	1613
Observations	5606	4187	19553	15908

Notes. This table reports the effect of crossing the population threshold on the within- and between-years retention of contract and permanent teachers. In column (1) the outcome variable is a dummy equal to one if the teaching position is filled by the same permanent teacher at the beginning (March) and the end (December) of a school year. In column (2) it is a dummy equal to one if the position is filled by the same teacher for two consecutive years (the teacher in school year t is the same teacher observed in year $t-1$). Columns (3) and (4) are the analogous of columns (1) and (2) for contract teaching positions. The sample includes all the teaching positions in rural Peru over the period 2016-2018 that are observed for at least two consecutive years. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the interval (?BW,0] (left-hand-side of the cutoff). SE are clustered at the school×year level. * p¡ 0.01, p¡0.05, and *p¡0.10.

Table B.8: Monetary Incentives and the Characteristics of Contract Teachers

	(1)	(2)	(3)	(4)	(5)
	Female	Age	Experience	Indigenous	University Degree
High Bonus	0.109	-1.302	-0.009	-0.006	0.075
	(0.060)	(0.864)	(0.024)	(0.127)	(0.054)
Mean dep. var. (Low Bonus)	0.578	37.363	0.950	0.358	0.294
Bandwidth	138.955	158.719	170.756	192.227	182.079
Schools	794	930	1007	1149	1072
Observations	1761	2115	2165	853	2306

Notes. This table reports the effect of crossing the population threshold on several teachers' characteristics. These are a female dummy (column 1), age (column 2), a dummy taking value 1 for teachers with at least 3 years of teaching experience (column 3), a dummy equal to 1 if the teacher speaks a Peruvian indigenous language (column 4), an indicator for university or technical institute education (column 5). The sample includes all contract teacher vacancies assigned in the 2015 and 2017 processes, regardless of whether they were assigned to certified or non-certified teachers. In column (4) the sample includes only vacancies assigned during the 2015 assignment process, as the same information is not available for 2017. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school×year level. *** p< 0.01, ** p<0.05, and *p<0.10.

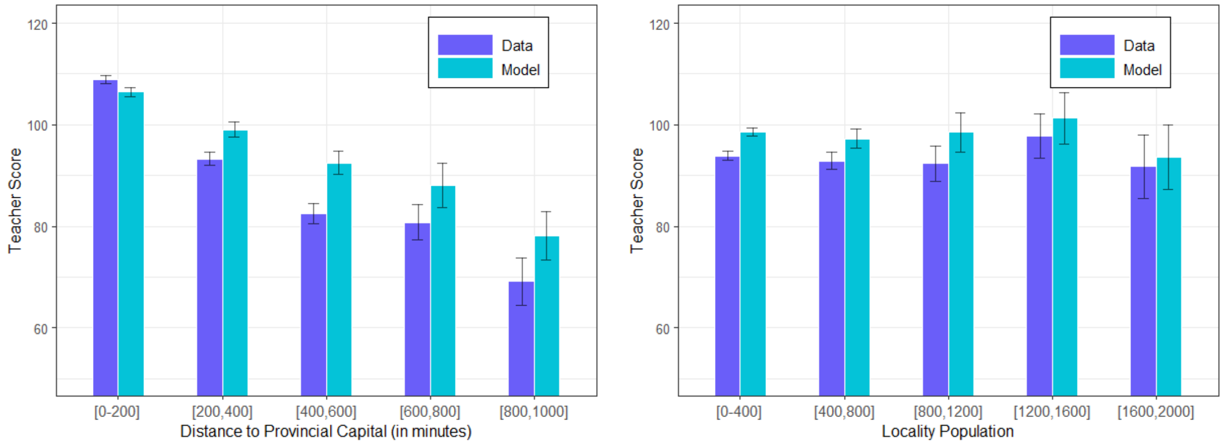
C Evidence from the Discrete Choice Model

Table C.1: Preference Estimates

Panel A: School/Locality Characteristics										
	Wage		Poverty Score		Infrastructure		Multigrade		Single Teacher	
	0.815	(0.120)	-0.201	(0.035)	-0.054	(0.054)	-0.237	(0.119)	-0.786	(0.192)
× Male	0.611	(0.157)	0.115	(0.032)	-0.060	(0.048)	0.019	(0.099)	0.519	(0.137)
× Experience $\geq$ 4	0.070	(0.053)	0.097	(0.036)	0.132	(0.052)	-0.284	(0.118)	0.020	(0.181)
× Urban	0.115	(0.061)	-0.060	(0.044)	0.036	(0.068)	0.009	(0.170)	-0.125	(0.242)
× Competent	0.170	(0.067)	-0.065	(0.047)	0.198	(0.076)	-0.782	(0.185)	-0.752	(0.351)
Std. Deviation	0.560	(0.053)								
	Bilingue		Vraem		Frontier					
	-0.747	(0.123)	-0.409	(0.284)	-0.747	(0.123)				
× Male	0.011	(0.113)	-0.234	(0.187)	0.270	(0.142)				
× Experience $\geq$ 4	-0.290	(0.112)	0.009	(0.247)	0.047	(0.155)				
× Urban	-0.050	(0.166)	0.017	(0.404)	-0.135	(0.319)				
× Competent	-0.732	(0.473)	-0.233	(1.063)	-0.048	(0.299)				
× Lives in Vraem			0.521	(0.208)						
Rural Wage Bonus Determinants (polynomial)										
log(Pop)	0.228	(0.301)			Time^3		-0.000	(0.000)		
Time	-0.207	(0.097)			Time × log(Pop)		-0.002	(0.028)		
log(Pop)^2	-0.054	(0.031)			Time^2 × log(Pop)		-0.002	(0.000)		
Time^2	0.011	(0.003)			Time × log(Pop)^2		0.007	(0.002)		
log(Pop)^3	0.002	(0.001)								
Panel B: Teacher-School Match Effects										
	Ethnolinguistic Match				Geographical Proximity (spline)					
Quechua × Quechua	1.488	(0.158)			Distance < 20km		-0.187	(0.003)		
Aymara × Aymara	1.375	(0.537)			20km < Distance < 100km		-0.033	(0.001)		
Ashaninka × Ashaninka	2.243	(0.558)			100km < Distance < 200km		-0.018	(0.001)		
Awajun × Awajun	2.086	(1.020)			200km < Distance < 300km		-0.017	(0.002)		
Other × Other	0.995	(0.113)			Distance > 300km		-0.002	(0.000)		
Panel C: Outside Option										
Constant	2.740	(1.197)			Quechua		0.527	(0.116)		
Male	0.840	(0.271)			Aimara		0.214	(0.454)		
Score	-0.205	(0.036)			Ashaninka		-0.564	(0.646)		
Age	0.019	(0.005)			Awajun		-0.026	(0.913)		
Experience	-0.043	(0.005)			Other Amazonas		-0.473	(0.067)		
Private Exp > 0	0.195	(0.054)			Time		-0.059	(0.008)		
					log(Pop)		0.115	(0.011)		

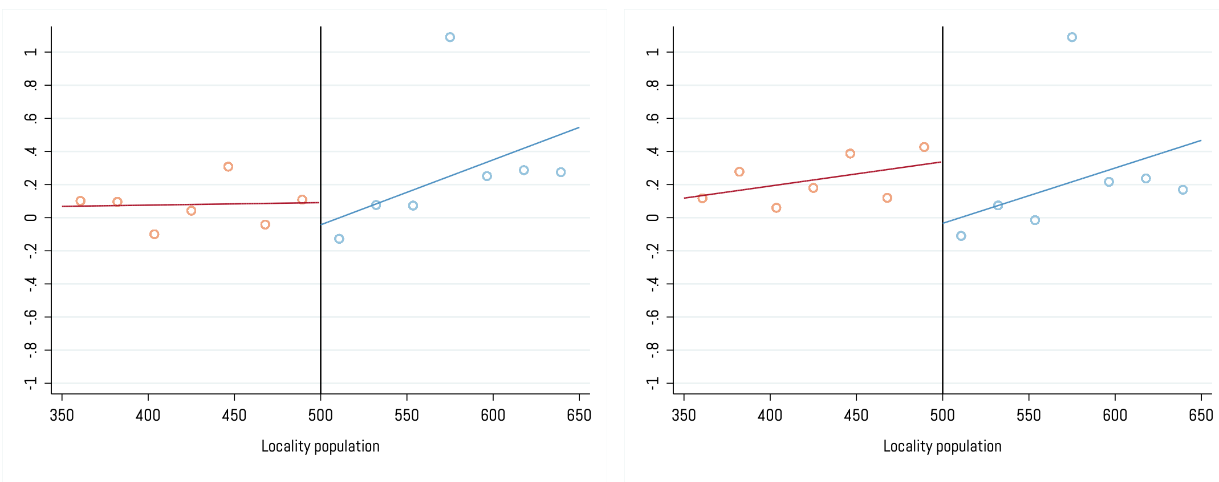
Notes. This table displays estimates and standard errors (in parentheses) of the parameters of the model described in Equation 2. Panel A shows the estimated coefficients associated to a selected set of schools/locality characteristics while Panel B shows estimated preferences for geographical proximty as well as the interaction between schools' language of instruction and teachers own native language. The data used contains choices of the pool of 59,949 applicants (note that 500 applicants are left out due to missing data) that participated in the allocation of short-term contracts for public primary schools in 2015. Estimation is done via maximizing the likelihood described in Equation 4 where the integral is computed numerically in an inner loop via a Gaussian-Hermite quadrature.

Figure C.1: Model Fit with Respect to the Competency Scores of the Assigned Teachers



NOTES. This figure uses simulated assignment data which is generated by running the serial dictatorship algorithm using predicting utilities computed from the estimates from Table 4 as well as a randomly drawn set of taste shocks ϵ_{ij}. It then compares the average score of teachers assigned to vacancies observed in the actual data and the simulated data depending on the associated school's distance to the provincial capital and locality population.

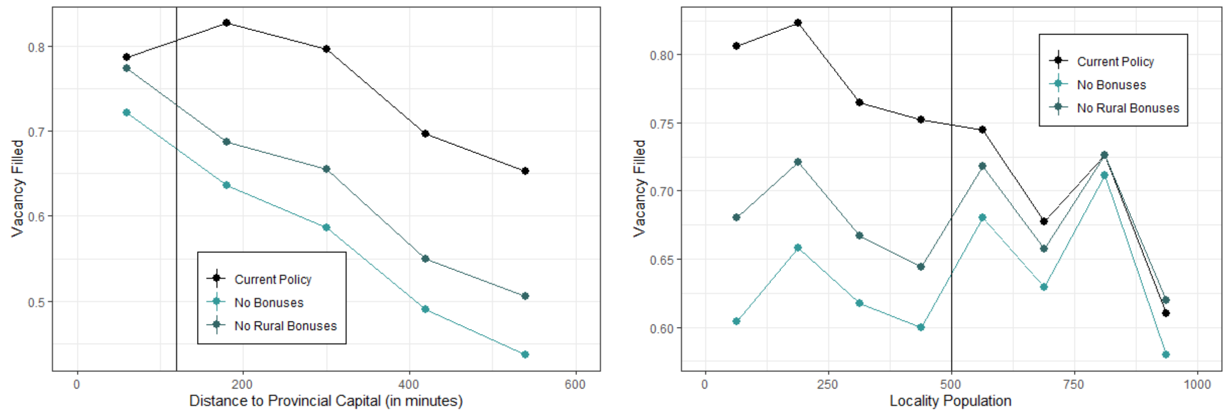
Figure C.2: Simulated Threshold-Crossing Effects With and Without Wage Bonus



a) Without Rural Wage Bonus **b) With Rural Wage Bonus**

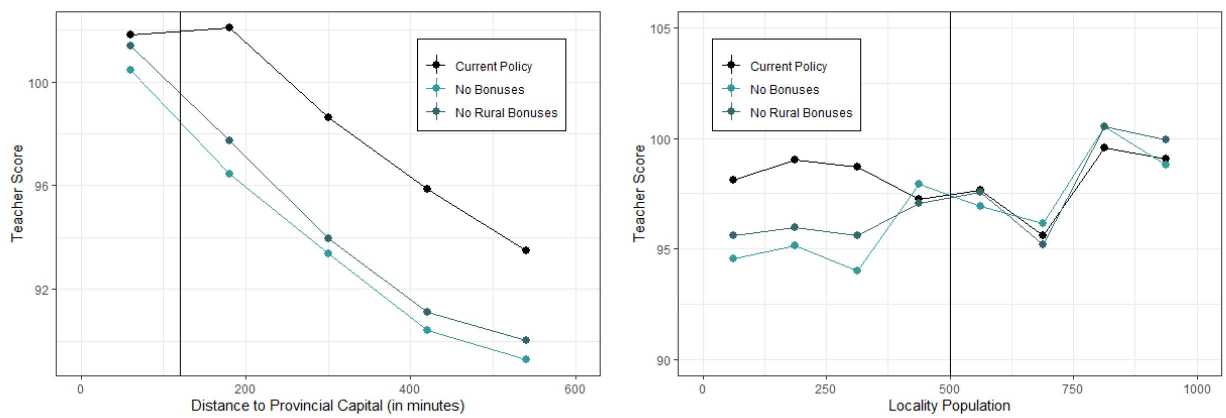
NOTES. This figure uses simulated assignment data which is generated by running the serial dictatorship algorithm using predicting utilities computed from the estimates from Table 4 as well as a randomly drawn set of taste shocks ϵ_{ij}. The counterfactual scenario depicted in Panel A is computed assuming the presence of all the existing wage bonuses except the S/ 500 rural wage bonus for localities with population smaller than 500 inhabitants and time-t-o-travel distance to the provincial capital higher than 120 minutes.

Figure C.3: The Effect of the Wage Bonus on Vacancy Filled



Notes. This figure uses simulated assignment data which is generated by running the serial dictatorship algorithm using predicting utilities computed from the estimates from Table 4 as well as a randomly drawn set of taste shocks ϵ_{ij}. It then compares, along the population and distance to provincial capital dimension, the average score of teachers assigned to vacancies under three counterfactual scenarios: (a) under the current policy, (b) in the absence of all wage bonuses, (c) in the absence of rural wage bonuses only.

Figure C.4: The Effect of the Wage Bonus on Teachers' Competency Scores



Notes. This figure uses simulated assignment data which is generated by running the serial dictatorship algorithm using predicting utilities computed from the estimates from Table 4 as well as a randomly drawn set of taste shocks ϵ_{ij}. It then compares, along the population and distance to provincial capital dimension, the share of vacancies filled under three counterfactual scenarios: (a) under the current policy, (b) in the absence of all wage bonuses, (c) in the absence of rural wage bonuses only.

D Alternative Wage Policies: Proofs

D.1 School Preferences Satisfy the Substitute Condition

Proof. Denote the set of all possible contracts $X = S \times T \times W$ where S is the set of schools, T the set of teachers we consider and W the set of wages that schools can propose. Under objective (i), we assume that T is the set of all teachers whereas we restrict T to be the set of high quality teachers under objective (ii). We assume that wages range discretely from the minimum wage proposed to teachers in Peru to an arbitrarily large upper bound.

Consider X' a subset of X. Define $C_s(X')$ and $R_s(X')$ the chosen set and the rejected set of school s. We assume WLOG that $C_s(X')$ is not empty. Otherwise this would imply, under (A1), that X' is also empty. Define w^* the wage offered in $C_s(X')$ and define $\underline{t}^*$ as the teacher with the lowest test score in $C_s(X')$. Under (A2), we know that w^* has to be the lowest wage offered in any of the contracts in X'. Consider now that we add an additional contract to X' such that $X'' = X' \cup \{(s, t, w)\}$. Under (A2), we know that if $w < w^*$ the new chosen set will be $C_s(X'') = \{(s, t, w)\}$ and the rejected set will be $R_s(X'') = R_s(X') \cup C_s(X')$. If $w > w^*$, the chosen set does not change $C_s(X'') = C_s(X')$ and the rejected set becomes $R_s(X'') = R_s(X') \cup \{(s, t, w)\}$.

If $w = w^*$, two cases may arise.

- If the size of $C_s(X')$ is strictly smaller than school s capacities, under (A1), we have that $C_s(X'') = C_s(X') \cup \{(s, t, w)\}$ and $R_s(X') = R_s(X'')$.
- If the size of $C_s(X')$ is equal to school s capacities (school s is at max capacity), under (A1) we have: (i) $C_s(X'') = C_s(X')$ and $R_s(X'') = R_s(X') \cup \{(s, t, w)\}$ if t is ranked lower than teacher $\underline{t}^*$, or (ii) $C_s(X'') = C_s(X') \setminus \{(s, \underline{t}^*, w)\} \cup \{(s, t, w)\}$ and $R_s(X'') = R_s(X') \cup \{(s, \underline{t}^*, w)\}$ if t is ranked higher than $\underline{t}^*$.

In any case, $R_s(X') \subseteq R_s(X'')$. □

D.2 Proposition 1

Proof. Under (A1)-(A2) stability implies that every school fills at least one vacancy for policy objective (i) and every school is matched with at least one high-quality teacher for policy objective (ii). Assuming that a given school has not reached the targeted policy objective would contradict stability given that schools would be willing to increase wages until they do so. Also, we know that the school-proposing generalized DA algorithm gives the stable allocation maximizing the individual welfare of the schools. This means that, conditional on stability, the sum of the wages offered is minimal, which proves part (i) of Proposition 1.

Given the wages offered, the matching outcome is stable also with respect to the priorities used in the initial mechanism. This implies that the same allocation can be implemented in the initial mechanism by fixing wages to the derived accepted wages, which proves part (ii) of Proposition 1.[36] □

[36] Under policy objective (ii), a similar argument applies when restricting the set of applicants to high quality teachers. However, given that low quality teachers have a lower priority than high quality teachers in the current mechanism, we can treat the allocation of the remaining vacancies to low quality applicants separately in order to simulate the equilibrium.